Spillover Effects of Mass Layoffs on Neighboring Firms

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Abstract

This paper examines the spillover effects of mass layoffs on neighboring establishments, shedding light on the dynamics of agglomeration economies. Leveraging comprehensive administrative data encompassing all entities in California, I study the indirect effects of mass layoffs on employment, earnings, and the number of nearby establishments. I exploit the geographic coordinates of establishments to define treatment and control areas based on their proximity to instances of mass layoffs. The findings reveal persistent and negative spillover effects on local employment levels four years after the events and a net decrease in operating establishments. However, there is no significant change in average earnings of workers. Furthermore, empirical evidence demonstrates that the spillover effects diminish with increasing spatial distance, effectively disappearing after 6km. Ultimately, I show industries closely interlinked to the event establishment exhibit more pronounced employment loss.

Keywords: Mass Layoff, Agglomeration Economies, Local Multiplier Effect

JEL codes: J21, J23, J24, J65, R12

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1 Introduction

There has been considerable research on the effects of opening large plants on the local economy, primarily started by Greenstone et al. (2010). Alternatively, a few papers have recently emerged to study the effects of plant closures on local economies (Gathmann et al. 2018; Jofre-Monseny et al. 2018; vom Berge and Schmillen 2022). Plant closures and mass layoffs have been a concern for policymakers, especially in the recent decades after the China shock (Autor et al. 2016; Autor et al. 2021). For instance, President Trump made retaining manufacturing jobs in the US one of the center points of his 2016 electoral campaign. One of his promises was to prevent the closure of the Carrier furnace plant in Indianapolis and the job loss of its 14,000 workers. Four years later, only 800 workers continued to work at the plant. Moreover, more than 20 manufacturing plants in the US had been closed by 2020.[1] Efforts to prevent the closure of large manufacturing plants extend beyond one administration. During the Great Recession, the Obama Administration allocated a substantial bailout of 80.5 billion dollars to the auto industry. Policymakers express two primary concerns regarding large mass layoffs and plant closures. First, there is direct job loss, which typically includes higher-paying positions. The second concern is the potential domino effect of mass layoffs on other local businesses interconnected with the large plant in various capacities. Throughout American history, there have been notable examples of company towns experiencing devastating consequences when their primary plant closed, affecting the entire community (Crawford, 1995). The negative impact of mass layoffs on directly displaced workers has been extensively studied (Jacobson et al. (1993); Couch 2001; von Wachter et al. 2009; Schmieder et al. 2009; Couch and Placzek 2010; Lachowska et al. 2018; Schmieder et al. 2023). However, the indirect effect on the close-by establishments[2] has been understudied and the evidence is contradictory.

The closure or significant downsizing of a large plant may have local negative effects on other establishments because of agglomeration economies, which refers to the advantages gained when firms and individuals co-locate in urban areas and industrial clusters (Glaeser

[1] Tony Cook, "Trump campaigned on saving jobs at Indianapolis' Carrier plant. This is what it's like now.", IndyStar, October 2020.

[2] Establishment is a business location which can be a part of a firm with multiple establishments (multi-establishment firm), or the single unit of a firm (single establishment firm).

2010). Economic activity in most regions is spatially concentrated. In the US by 1992, only 1.9 percent of the land was built up or paved (Burchfield et al., 2006). The automotive industry in the Midwest, finance in New York, and high tech in the Bay area are the most notable examples of agglomeration economies in the US. Agglomeration economies benefit employers and employees through thick labor markets (labor market pooling), knowledge spillovers, and input-output linkages (Marshall 1920; Ellison and Glaeser 1997; Ellison et al. 2010; Combes and Gobillon 2015). When a large establishment experiences closure or mass layoff, on the one hand, local labor markets and industry linkages can be interrupted and decrease other establishments' productivity and employment. Another potential channel of negative spillover is the local multiplier effect, in which the creation or destruction of jobs may create or destroy other jobs in the non-tradable sector through changes in local demand (Moretti, 2010). On the other hand, mass layoffs suddenly increase local labor supply and, therefore, may put downward pressure on wages, resulting in more hiring and positive spillover effects. In this paper, I study the spillover effects of large mass layoffs on neighboring establishments in California and shed light on the mechanisms that cause them.

Studying the spillover effects of mass layoffs requires an extensive administrative dataset encompassing establishments in an economy.[3] In this research, I leverage the establishments' longitude and latitude information in California's Quarterly Census of Employment and Earnings (QCEW) from 2000 to 2019. This comprehensive administrative data contains establishments covered by California unemployment insurance, containing over 95% of the state's employees. To define mass layoffs, I adopt a modified version of the definition used by Gathmann et al. (2018). Accordingly, a mass layoff is characterized by an employment reduction of a minimum of 500 employees. Additionally, I employ a 30 percent decline in year-to-year employment, drawing from the literature on mass layoffs and displaced workers.[4] By this approach, I ensure substantial job losses within the local economy and the event establishment.

[3]While alternative datasets like Dun and Bradstreet also provide location information at establishment-level data, there are concerns about self-reporting and imputation issues. Another concern about such datasets is successors and predecessors of establishments, which are especially important for defining mass layoff events, which are the centerpiece of this study.

[4]In the literature of the effects of mass layoffs on displaced workers, 30% drop in employment level is the gold standard in defining mass layoff events (Jacobson et al. 1993; Couch 2001; von Wachter et al. 2009; Schmieder et al. 2009; Couch and Placzek 2010; Lachowska et al. 2018; Schmieder et al. 2023)

I employ a difference-in-differences event study approach to assess the causal impact of mass layoffs on neighboring establishments.[5] Given the critical role of the distance between the event and affected establishments[6], I move beyond conventional geographic boundaries (e.g., counties, municipalities) and consider the precise distance between the event establishment and its neighboring counterparts. Consequently, the treatment area is defined as a circular region with the mass layoff establishment at its center. The primary shock in the treatment area is a sharp decline in operations and employment of a large establishment (with at least 500 employees). Suppose changes in labor market thickness, breakage of input-output linkages, and a decrease in local demand impact the nearby establishments. In that case, the control area should have a similar establishment at its center to be a viable counterfactual to simulate these economic connections. Thus, the control group is constructed as a circle encompassing a similar-sized and industry-aligned large establishment to the event establishment.

In this paper, I show that a large mass layoff negatively impacts the employment levels of neighboring establishments over the four years following the event. First, I establish that the magnitude of this effect diminishes as establishments are located farther away from the event, eventually reaching zero at a distance of greater than 6 kilometers. Based on these findings, I define treatment and control groups using a radius of 6 kilometers, representing the range within which the spillover effects are most pronounced. Upon analyzing employment dynamics, I find that, excluding the event establishment, the employment level in the treatment area is 6 percentage points lower compared to the counterfactual after four years. Additionally, my results indicate that within the treatment area, there is a reduction of 3 percentage points in the number of establishments compared to the control group. Total paid earnings (payroll) declined by 9 percentage points; however, I do not find statistically significant changes in average earnings per employee.

Furthermore, I employ economic distance indexes to search for the underlying three agglomeration channels driving the spillover effects. Specifically, I utilize industries' input-output index for input-output linkages, occupation correlation between industry pairs for

[5]In Section (4), I address and discuss the emerging literature in difference-in-differences.

[6]I do not examine outcomes of neighboring residents of mass layoff events. However, in Appendix C, I examine changes in the prices of single-family homes.

knowledge spillover, and rate of workers' movement between industry pairs (i.e., employment flow) for labor market pooling. Then, I categorize establishments based on their economic proximity to the event establishments. The findings of this analysis reveal intriguing patterns. In all three measures, the industries economically closest to the event establishments experience a notable employment decline in their employment. In contrast, the employment of industries economically furthest away experienced close to zero changes in all measures. These results suggest that interruption in agglomeration economies is an important channel behind the decline in employment. Moreover, I examine the channel local multiplier effect by studying the disparities in spillover effects by tradability of events and affected establishments. My findings show that if the event establishment is in the tradable sector, the non-tradable employment declines by 4.4%. In contrast, a mass layoff in the non-tradable sector has no statistically significant impact on the tradable sector's employment.

The topic of the indirect effect of mass layoffs remains relatively understudied but is gradually expanding. To the best of my knowledge, three papers currently address this topic, each yielding contradictory findings. Two of these papers observe positive spillover effects on local employment, contradicting my findings. Jofre-Monseny et al. (2018) analyze the spillover effect of 45 closures of manufacturing plants in Spain and uncover positive job creation for each lost job within the local economy. Vom Berge and Schmillen (2022) examine German data and reveal a 5% increase in local employment (excluding the event) five years after the mass layoff event. Similar to my work, they include all industries but use a smaller 50-employee threshold to define mass layoff. Conversely, another paper on the German economy presents evidence of a negative indirect effect on employment. Gathmann et al. (2018) studied West Germany and found a negative employment effect of 2% on the local economy. They use a 500 threshold for the mass layoff definition; however, the area examined for the spillover effect is larger than my setting. Contradictory results suggest that the size of shock and labor market conditions matter in the direction of the effects. Therefore, studying other major economies and more deeply analyzing the potential channels of positive or negative spillovers is necessary.

With this paper, I contribute to the existing literature as the first study investigating the spillover effects of mass layoffs in the United States economy. I employ a novel approach in defining the control group, enhancing the robustness of my analysis, and providing valuable insights into the specific context of the US labor market. Furthermore, for the first time, I move beyond aggregate-level analysis and study establishment-level outcomes to better understand employment effects at intensive margins. Establishment level analysis also enables the analysis of the heterogeneity among different types of establishments, which has not been previously studied. This paper is among just a few papers that use administrative QCEW data, and specifically its information on geographic coordinates, which can be followed by more research at the intersection of labor and spatial economics. Finally, it is the first paper that quantitatively examines each agglomeration channel.

In the bigger picture, my paper contributes to the existing body of research that aims to quantify and comprehend the spillover effects of (mostly positive) local economic shocks through agglomeration forces (Ellison and Glaeser 1997; Rosenthal and Strange 2004; Greenstone et al. 2010; Kline and Moretti 2014). In their canonical work, Greenstone et al. (2010) demonstrate that opening large manufacturing plants leads to a significant and positive increase in productivity within their host counties. Employing a treatment and control group framework, they assess the change in total factor productivity by treating counties that successfully attract large manufacturing plants as the treatment group and comparing them with the control group consisting of counties that were not selected. In a related study, Kline and Moretti (2014) examines the long-term effects of the Tennessee Valley Authority program on local economies. Their findings indicate positive impacts on productivity, employment, and aggregate earnings, suggesting that the local economy benefited from the program. Furthermore, Feyrer et al. (2017) investigate the employment and wage effects at the county level of the new oil and gas production facilities resulting from fracking technology. Their research also reveals positive effects on both employment and earnings.

This paper also contributes to another literature that studies local economic shocks through the lens of local demand changes. Moretti (2010) calls this phenomenon the local multiplier effect and shows that creating tradable jobs in an American city causes more job creation in the non-tradable sector. Moretti and Thulin (2013) show similar multiplier effects for Swedish cities and van Dijk (2017) for US cities. Faggio and Overman (2014) show that in England, the multiplier effect of public job creation on total private employment is zero, but it is similar to other studies on the non-tradable sector. I contribute to this literature by studying the heterogeneity in the tradability of the event and affected establishments.

The remainder of the paper is organized as follows. Section 2 provides a conceptual framework that explains how mass layoffs can impact local labor markets. Section 3 defines mass layoffs and describes the data structure employed in the analysis. Section 4 explains the identification, employing the difference-in-differences approach and main results. Section 5 presents empirical evidence for the spillover channels. Finally, Section 6 serves as the paper's conclusion, summarizing the key findings and offering insights for future research.

2 Conceptual and Theoretical Framework

As in many other countries, economic activity exhibits significant concentration in the United States. Marshall (1920) argues that firms and workers derive numerous benefits from agglomeration, primarily through a thick labor market, input-output linkages, and knowledge spillover.

A thick labor market offers advantages to both employers and employees. A larger pool of potential candidates for firms increases the likelihood of finding high-quality matches for job openings and decreases searching time (Andersson et al. 2007; Andini et al. 2013; Abel and Deitz 2015). Conversely, job seekers benefit from the higher chances of finding suitable positions when multiple firms actively hire within the same area. Furthermore, the concentration of firms improves input-output linkages, facilitating access to diverse sellers for necessary inputs (Faggio et al. 2017). This broader range of suppliers results in a higher probability of obtaining higher-quality inputs at lower prices. On the output side, whether intermediate or final goods, the diversity of buyers enhances market opportunities for establishments. Additionally, the geographic proximity of upstream and downstream firms leads to cost and time savings in transportation, further boosting efficiency within the agglomerated region. Knowledge spillover represents another source of agglomeration benefits. As the concentration of workers increases in a local economy, interactions and the flow of employees between firms become more frequent. Increased collaboration and knowledge-sharing among workers lead to increased human capital within the workforce, ultimately driving higher productivity levels (Black and Lynch 1996; Combes and Duranton 2006; Serafinelli 2019).

What are the possible scenarios in which plant closures or mass layoffs can affect neighboring establishments through agglomeration economies? When such events occur, they can disrupt input-output linkages within the local economic network. A large firm could be a part of the production chain in the area, with other related firms positioned either upstream or downstream relative to the event firm. Upstream firms supply goods and services to the event firm and a reduction in the size of the firm results in decreased demand for the final products of these upstream firms. Conversely, some downstream firms rely on the goods and services provided by the event firm. The absence of the event firm's products necessitates sourcing from geographically distant firms, increasing production costs for the downstream firms. Such interruptions in input-output linkages can profoundly affect neighboring establishments' profit and employment levels. The demand reduction and increased production costs can lead to decreased profitability and potential job losses in the affected establishments.

Large mass layoffs also affect the total factor of productivity. First, large mass layoffs decrease the size of the area's labor market, resulting in lower quality employer-employee matches and lower productivity. Second, a reduction in the number of workers reduces the flow of workers between firms and different sorts of interactions and affects knowledge spillover among workers. This is important for industries with higher levels of technology and innovation (Moretti 2021; Saxenian 1996).

Agglomeration forces are not the only reasons that mass layoff events can have a spillover effect on other establishments. The second channel is local multipliers. After a mass layoff, local establishments lose some demand for their products. The employees who used to buy local goods and services during workdays are no longer in the area, which translates to a reduction in local demand and can cause more layoffs. The magnitude of the local multiplier varies between tradable and non-tradable sectors. In the non-tradable sector, the demand comes from the local market, meaning the goods and services the laid-off workers purchased have at least partly vanished. The demand effect on the tradable sector is more limited since the affected establishments can find customers outside the local market.

2.1 A Simple Agglomeration Model

I use a simple model developed by Gathmann et al. (2018) from Glaeser and Gottlieb (2009) to formalize the spillover effect of mass layoffs on local employment earnings. I assume that all establishments have a Cobb-Douglas production function in which there are two types of capital, fixed ($\bar{K}_j$) and fully flexible (K_j) with the share of μ:

$$Y_j = f_j A_r L_j^{\alpha} \bar{K}_j^{(1-\alpha)(1-\mu)} K_j^{(1-\alpha)\mu}, \tag{1}$$

where f_j is the productivity shifter of firm j, $A_r = L_r^{\lambda}$ is the productivity shifter of the local area, with λ representing local productivity links (input-output linkages, knowledge spillover, local labor pool, etc.). By taking the first order condition of capital and labor, I can derive the aggregate demand curve:[7]

$$\log L_r = \log \sum_j L_j = \log \sum_j f_j^{\frac{1}{(1-\alpha)(1-\mu)}} + \frac{\log A_r}{(1-\alpha)(1-\mu)} - \frac{1-(1-\alpha)\mu}{(1-\alpha)(1-\mu)} \log w_r + \kappa. \tag{2}$$

Following Gathmann et al. (2018), I can study the overall effect on aggregate local labor demand by total differentiation of (2):

$$d \log L_r = \underbrace{\frac{df_{\text{event}}}{J(1-\alpha)(1-\mu)}}_{\text{direct effect } (-)} + \underbrace{\frac{\lambda}{(1-\alpha)(1-\mu)} d \log L_r}_{\text{agglomeration spillover } (-)} \underbrace{- \frac{1-(1-\alpha)\mu}{(1-\alpha)(1-\mu)} d \log w_r}_{\text{endog. wage adjustment } (+)}. \tag{3}$$

Excluding the unambiguously negative direct effect on the event establishment, there are two opposite forces that affect the aggregate local employment:

1. Agglomeration spillover on nearby establishments (< 0): The magnitude of agglomeration effect depends on the economic closeness (λ) of the industry of the event establishment and other firms. Industries that are economically closer to the event establishment would be affected the most.

2. Local wage adjustment due to the increase in available labor from the mass layoff

[7] $\kappa = -(\mu/(1-\mu)) \log i + \log \bar{K} + (1-(1-\alpha)\mu)/((1-\alpha)(1-\mu)) \log \alpha + (\mu/(1-\mu)) \log[(1-\alpha)\mu]$

establishment (> 0): The magnitude of the wage adjustment depends on the relative size of the mass layoff to the size of the workers' commuting zone, and how mobile are workers in response to unemployment to move to more prosperous areas. If the size of employment reduction is small relative to the commuting zone, and/or workers are highly mobile, decrease in earnings would be small and the positive effect of the wage adjustment can go to zero.

Thus, the direction of the spillover effect is ambiguous and depends on the local labor market and industry composition. I focus on the spillover effect on this paper, and do not quantify each section of equation (3); however, I use it to explain my findings and contrast them with the results from the existing literature.

3 Data

The primary dataset that I use is the administrative Quarterly Census of Employment and Wages (QCEW) of California which includes comprehensive information on establishments that are covered by the California Unemployment Insurance (UI) system and federal entities covered by the Unemployment Compensation for Federal Employees (UCFE) program. QCEW reports monthly employment and quarterly total paid earnings of each establishment. Two crucial pieces of information in QCEW make it possible to study the spillover effect of mass layoffs. The first is geographic coordinates (longitude and latitude) of establishments. By having the coordinates information on establishments, I can find the exact location of the mass layoff establishments and their distance to other establishments. About 90% of establishments have proper geocoded information, and the other 10% are dropped from the sample.[8] The second piece of information which is essential for any mass layoff study is observing successors (and predecessors) of establishments. With observing successors and predecessors in QCEW, I do not treat establishments that only experience a change in their identification without employment loss, as a mass layoff event.[9] QCEW also contains 6-

[8]The distribution of employment, earnings, and industry of excluded establishments are not different from the rest of the sample.

[9]Change in establishment identification number can be due to various reasons such as a change in ownership, merges, divergence, or simply accounting reasons.

digit NAICS industry codes, essential to analyze agglomeration forces and heterogeneity in Section 5.

The second dataset I utilize is the Quarterly Earnings (QE) of California, which are employer-employee matched data showing the quarterly earnings of workers covered by UI from each employer. QE is at the firm level, unlike the QCEW, which is an establishment-level dataset. Therefore, I cannot directly match all workers to their workplace other than single establishment firms. I employed data from both sources from 2000 to 2019 to ensure the analysis remains unaffected by the pandemic era shocks. Finally, I transformed both data sources into annual longitudinal datasets to prevent treating seasonal layoffs as mass layoff events.[10]

3.1 Mass Layoff Definition

To identify an employment reduction incident as a mass layoff, two key restrictions must be met: (1) There must be a 30 percent reduction in the annual employment level at the event establishment. This benchmark is borrowed from existing literature on the effect of mass layoff on displaced workers to ensure that it reflects a sizable reduction in economic activity (Jacobson et al. 1993; Couch 2001; von Wachter et al. 2009; Schmieder et al. 2009; Couch and Placzek 2010; Lachowska et al. 2018). (2) The mass layoff must involve a minimum of 500 employees within a year, as defined by Gathmann et al. (2018). It is important to note that in the QCEW data, we do not distinguish between full-time and part-time workers; the employment count encompasses all worker types.

Furthermore, establishments in the agricultural sector are excluded from mass layoff establishments. However, they are still considered part of the sample for assessing the impact on the local economy. The sample of mass layoff establishments is confined to the period from 2004 to 2015. This duration allows for a four-year observation window, enabling the analysis of pre- and post-event trends. Once an event establishment experiences a mass layoff, it should not recover its employment levels to the pre-event period. In situations where an establishment experiences multiple mass layoff incidents, we only consider the first.

[10] Seasonal layoffs do not occur as productivity shock but due to the nature of the industry. Thus, not including them in an analysis based on productivity shocks is preferred.

3.2 Statistics of the Mass Layoff Establishments

Following the definition in 3.1, 132 mass layoffs occurred between 2003 and 2015. Among all events, 53 eventually get closed by 2019, which on average takes 3.5 years from the event year. Similar to economic activities, mass layoffs are also concentrated in a few areas, mainly in the greater Los Angeles area, Bay Area, and, to a lesser extent, San Diego and Sacramento counties. These establishments are larger than a typical one in California, and also, as we can see in Figure 1, pay higher wages to their employees. Higher wages suggest that these establishments have a higher share of skilled workers, which is essential for regional productivity.

One assumption in 2.1 was that the mass layoff shock represents a decline in firm-specific productivity. However, there is a concern that mass layoffs are due to local-industry shocks. In Appendix A I show that local economic conditions and state-level industry shocks do not predict large mass layoff incidences.

Previous studies examining both positive and negative employment shocks on the local economy have primarily focused on the impact on the tradable sector (e.g., Greenstone et al. 2010; Moretti 2010; Jofre-Monseny et al. 2018; Gathmann et al. 2018). However, my study delves into the effects of mass layoffs in all sectors on the local economy. Table 1 displays the wide range of industries where these mass layoffs have occurred.

To use mass layoff events as a productivity shock to nearby establishments, it is vital to ensure persistent employment decline in event establishments. Figure 2 panel (a) presents the average employment level eight years before and after the event. Notably, the employment level shows an increasing trend before the event, but at the time of the event, there is a sudden and mechanical decline in employment levels. Even eight years after the event, the employment level (excluding closures) has not fully recovered to the pre-event period, indicating that, on average, the mass layoffs in the sample have resulted in permanent job losses. Figure 2 panel (b) illustrates the log of the average earnings per employee. Before the event, the average earnings per employee remained relatively stable. However, in the post-event level, we observe an increase in earnings, suggesting that, on average, a higher share of lower-skilled workers were affected and laid off during the mass layoffs.

4 Identification and Results

In this paper, I employ a difference-in-differences approach, which requires a control area ideally identical to the treated one before the mass layoff event. The critical element in each treated area is the event establishment and its economic linkages with nearby establishments before the mass layoff. To construct a counterfactual, I undertake a simple matching process. These counterfactuals must meet four criteria: (1) be in the same industry as the event (at least 2-digits NAICS code), (2) exhibit persistent employment trend over nine years of observation with no mass layoff, (3) be in a different commuting zone (CZ), and at least 30 km away from the event, and (4) have at least 300 employees at the time of the event.[11]

While traditionally, studies on the spatial spillover effect of local shocks have treated space as a discrete concept (Jofre-Monseny, Sánchez-Vidal, and Viladecans-Marsal 2018; Gathmann, Helm, and Schönberg 2018), I take a different approach by treating space as continuous, leveraging the geocoded data. This choice is crucial because the impact of mass layoffs depends on the spatial distance between the event establishment and the affected ones rather than being limited by administrative boundaries. To achieve this, I consider the treated area a circle with the event establishment at its center. Similarly, the control region is a circle around the counterfactual establishment.

In Section 4.2, I discuss how the radius for treated and control regions (R^T and R^C) are chosen, but first, I explain the overall structure of the difference-in-differences design. I have a staggered difference-in-differences[12], in which there are 132 pairs of treatment and control[13] regions at the industry level, with events occurring at different times.

In recent years, there has been a growing body of literature expressing concerns regarding staggered difference-in-differences designs (de Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Gardner 2021).[14,15] In summary, the

[11] 16 establishments are counterfactual for more than one event. There are 97 unique counterfactuals for 132 mass layoff events.

[12] staggered design refers to settings in which observations in the treated sample are assigned treatment at different points in time

[13] Some control regions are duplicated, but they are not necessarily at the same event time.

[14] For a comprehensive overview of the current developments in this literature and practical recommendations, please refer to Roth et al. (2023).

[15] In Section 4.3, I examine the difference-in-differences results using suggested methods provided by Sun and Abraham (2021), Gardner (2021), and Callaway and Sant'Anna (2021) and compare them with the

main issues are heterogeneity in the effects by time of the event (or policy adoption) and group, as well as contamination of coefficients by effects from other periods. For example, de Chaisemartin and D'Haultfœuille (2020) demonstrate that regression coefficients may appear negative even when all the average treatment effects (ATEs) are positive, and Sun and Abraham (2021) argues that coefficients can be influenced by the effects of other time periods. To address these potential issues, I have implemented several precautionary measures. Firstly, in cases where treatment circles overlap, I have excluded establishments that received treatment more than once. Secondly, I have removed all establishments within regions with overlap between treatment and control areas. Consequently, the regression sample exclusively comprises establishments treated only once in the treatment group and establishments that have never been treated in the control group. Lastly, I have restricted comparisons to treated and control industries within the same cohort, ensuring that problematic comparisons[16] are avoided. Therefore, for each mass layoff case, an industry in the treatment region is compared with the same industry in treatment regions. While these steps mitigate some methodological concerns, I also demonstrate in Section 4.3 that my baseline regression results align qualitatively with the methods suggested in recent papers.

4.1 Spatial Decay of Spillover Effect

The first two questions to answer are: On average, is there a spillover effect post-event, and the relationship between distance and potential spillover effects? To answer these two questions, I employ a methodology involving creating five concentric "donut" treatment areas around each event establishment, ranging from 0 to 10 kilometers, and utilize a circular region surrounding the counterfactual establishment as the control group (Figure 3). This framework allows me to estimate the following difference-in-differences regression for each treatment "donut" :

$$Y_{irt} = \beta_1 Treatment_r + \beta_2 Post_t + \beta_3 Treatment_r * Post_t + \mu_i + \delta_r + \gamma_t + \epsilon_{irt}, \qquad (4)$$

baseline results from my main identification.

[16]Problematic comparisons are cases such as comparing treated with not yet treated or already treated.

where Y_{irt} is the log employment of industry i in region r at year t. $Treatment_t$ indicates being in the treatment region (2 km donuts in this case), and $Post_t$ indicates being after the event year. β_3 is the coefficient of interest representing the potential spillover effects.

I use three different control radii of 5, 6, and 7km and estimate equation (4) to ensure the results are not sensitive to the control radius. Figure 4 displays the average spillover effect of mass layoffs by distance for three control radii. A negative spillover effect is observable irrespective of the control area radius, with its magnitude diminishing as the distance from the event increases. Beyond the 6 km threshold, the spillover effect approaches zero and becomes statistically insignificant. This suggests that, on average, the spillover effect is present within a 6 km radius of the mass layoff event.

Comparison of Treatment and Control Regions Following the results of equation (4), from now on, all the analyses in this paper use a 6 km radius as the radius around events (and counterfactual) for treatment (and control) regions. Tables 2 and 3 compare treatment and control regions. On average, establishments in treatment regions are slightly larger and older but pay lower earnings. The industry structure of treatment and control areas is almost identical. The only difference comes from information and other services sectors where treatment areas have lower and higher shares, respectively, compared to control regions. These summary statistics ensure that treatment and control areas are comparable.

4.2 Event Study

I employ a difference-in-difference event study approach to estimate the spillover effect of the mass layoff by using the following reduced-form regression:

$$Y_{ir\tau t} = \sum_{\tau=-4}^{-2} \alpha_\tau Event_{r\tau t} + \sum_{\tau=0}^{4} \beta_\tau Event_{r\tau t} + \mu_i + \gamma_t + \delta_r + \lambda_\tau + \epsilon_{ir\tau t}, \tag{5}$$

where Y_{irt} is the labor market outcome of interest, and τ represents the time relative to the year of mass layoffs ($\tau = 0$). $Event_{r\tau t}$ is a binary variable that is 1 for the treatment region at time τ and 0 otherwise. This regression controls for industry, region, year, and relative time fixed effect. The year fixed-effect control general shocks such as business cycles, together with relative time fixed effects, guarantee that changes in the outcome of interest in the treatment group are compared with the control group at the same calendar and relative year. Time-invariant differences among regions and industries are controlled by region fixed effect (δ_r) and industry fixed effect (μ_i). The standard errors are clustered at the regional level.

In difference-in-differences models, the parallel trends is a key assumption, and parameters α_{-4} to α_{-2} show if the parallel trends assumption holds in this empirical setting. The parameters of interest are β_0 to β_4 that indicate the percentage change of the dependent variable for each relative year after the event.

4.2.1 Baseline Results

Employment and Earnings.[17] Figure 5 presents the baseline results of regression (5) for the key labor market outcomes: employment, total paid earnings, and earnings per employee.[18,19] The parallel trends assumption holds for all outcomes, as the point estimates are close to zero and statistically insignificant. In panel (a), we observe that employment in treated regions begins to decline in the year of the event, with a more pronounced drop one year after the event. Subsequently, employment continues to decline at a lower rate in the post-event years, showing 6 percentage points decline four years after the event. As expected, the same pattern is observed for total earnings in panel (b), as it is a function of the number of employees. The total earnings follow a similar trend, declining in the year of the event and continuing to decrease at a reduced rate in the post-event years.

In panel (c), the average earnings per employee results shed light on the theoretical ambiguity discussed in section 2.1 regarding the direction of spillover effects in which a decrease in earnings could have a positive spillover effect on employment. Interestingly, the point estimates of earnings per employee in the post-event years are consistently lower in treated regions compared to control regions. However, they are less than 1 percentage point and statistically insignificant. This finding suggests that the local wage effect of mass layoffs

[17] In Appendix D, I examine the impact of mass layoffs on housing prices.

[18] Earnings per employee is calculated at the establishment level by dividing total paid earnings by total employment.

[19] In Appendix B, I study the effects of mass layoffs on directly displaced workers. The results are consistent with previous literature showing persistent drop in employment and wages of displaced workers.

is negligible in the sample, indicating the absence of a positive spillover channel.

Finally, in Table 4, I summarize the event study results along with various alternative controls. In columns (4), (8), and (12), I exclude Industry fixed effect, but the overall post-event trends are consistent with the main model in columns (1), (5), and (9). Furthermore, the results are robust to including year-industry and region-industry interactions in the model.

Employment Decline at The Extensive Margins. Is the decline in the employment of treated areas relative to control due to net layoff in existing establishments, increase in closures, decrease in openings of businesses, or a combination of all? I investigate the changes in the net employment change of existing establishments in 4.2.2. However, I can analyze changes in the number of establishments to understand the role of business formation and closures in the decline of employment in local areas. Figure 8 displays the results of regression (5) with the number of establishments as the dependent variable. Prior to the event, there is an upward trend indicating openings exceeded closures more rapidly in the treatment areas compared to the control. However, after the event, the trend inverses, and four years later, the number of establishments is 3.1 percentage points lower. While changes in the number of establishments do not estimate the exact extensive margins of employment change, it is a proxy providing evidence for that.

4.2.2 Establishment Level Results

Up to this point, I have conducted an aggregate-level analysis of the spillover effects within a 6km radius around the event. However, a crucial dimension of the mass layoff shock that remains unexplored in the existing literature pertains to the spillover effects at the establishment level. To exclude factors related to establishment openings and closures and concentrate solely on the shifts occurring within existing establishments, I limit the sample to include only those establishments present in the data one year before the event and up to four years afterward. Moreover, I modify regression (5) into the following:

$$Y_{eir\tau t} = \sum_{\tau=-4}^{-2} \alpha_\tau Event_{r\tau t} + \sum_{\tau=0}^{4} \beta_\tau Event_{r\tau t} + \mu_i + \gamma_t + \delta_r + \lambda_\tau + \omega_e + \epsilon_{eir\tau t}, \quad (6)$$

where ω_e is the establishment fixed effect.

Figure 8 and Table 5 present the findings of the equation (6). In Panel (a), Columns (1) and (2), the results indicate that for firms that survived up to four years after the event, employment begins to decrease in the year of the event and continues to decline by 2.4 percentage points three years after that. Although there is a subsequent employment increase in the fourth year, it remains 2.1 percentage points below the control group. Notably, the extent of employment reduction is less than half of the aggregate results observed. Moving to Panel (b) and Columns (3) and (4), the pattern for total paid earnings is less persistent compared to employment. Total paid earnings experience a decline until the second year, but they begin to rebound by the third year and become statistically insignificant by the fourth year. The different post-event patterns of total paid earnings compared to employment would make sense by examining earnings per employee in Panel (c), Columns (5) and (6). A modest upward trend is noticeable, albeit statistically insignificant, two years post-event. These outcomes suggest that these establishments tended to lay off lower-skilled employees and likely hired more higher-skilled workers following the shock.

The establishment-level analysis allows for a more nuanced examination of heterogeneity based on establishment characteristics. Firstly, I investigate disparities in spillover effects by the industry of the event and affected establishments. Although the aggregate findings indicate persistent employment loss in nearby establishments, different industries may exert varying effects on local areas and respond differently to mass layoff events. Figure 9 presents the results of equation (6) broken down by the industry of the event establishment.[20] To address suppression requirements, industries with similarities are grouped. In sectors where agglomeration economies play a significant role, such as mining-utilities-construction-

[20]Given that there are only 132 mass layoff events, I combine industries with similarities into groups to comply with suppression requirements of the Employment Development Department. NAICS codes 21-23, and 31-33 are combined into Mining, Utilities, Construction, and Manufacturing; 42, 44, 45, 48, and 49 are trade and transportation; 51-56 are Office and Professional Services; 61, and 62 are health and education; 71, and 72 are entertainment and food; 81, and 92 are public and other services.

manufacturing and professional services, a decline in employment is observed following the event year. Conversely, mass layoffs in the health and education sector do not lead to significant employment declines. Notably, the entertainment and food sector results are intriguing; since these industries heavily rely on local demand, the closure of a large establishment can create opportunities for other establishments in the same sector to expand their local market share. After a mass layoff event in this sector, employment increases by 2.5 percentage points in the first year, with subsequent point estimates remaining positive albeit insignificant.

Moving on to disparities in affected industries, Figure 10 demonstrates that regardless of the sector of the affected establishments, employment declines after the event. While mining-utilities-construction-manufacturing, trade-transportation, and food-entertainment sectors experience recovery four years later, establishments in other sectors do not bounce back post-event.

Secondly, I employ different measures to explore how establishment quality can determine resilience towards exposure to mass layoffs. Three notable establishment characteristics serve as proxies for establishment quality: firm size[21], single vs. multi-establishment firms, and firm age. Firm size, often regarded as a proxy for firm quality[22], is depicted in Figure 11 panel (a). The data show that surviving establishments associated with small firms (1-9 employees) have experienced the hardest hit. Medium-sized firms (10-100 employees) experienced slightly less impact than small firms, although the difference is not particularly noticeable. In contrast, changes in employment among large firms (more than 100 employees) were insignificant and less than half of the impact observed in small and medium-sized firms. A similar pattern is evident when establishments are categorized as single or multi-establishment firms. Single-establishment firms experience nearly double the employment decline compared to multi-establishment firms, which aligns with the results based on firm size.

The third measure of establishment quality is firm age, calculated one year before the

[21] I specifically choose firm size over establishment size because a small establishment can be associated with a large firm and benefit from its resources, and perform differently from a small single establishment firm.

[22] See Productivity in SMEs and large firms in OECD Countries.

event. Figure 11 panel (c) demonstrates that young firms (1-5 years) were the most affected, while older firms (more than 6 years) fared better. Interestingly, firms over 11 experienced greater employment loss than those aged 6 to 10 years. One possible interpretation is that the oldest firms had established strong connections with event establishments and were more dependent on them. In contrast, younger firms, as previous studies have suggested, were more sensitive to the shock.

4.3 Sensitivity Analysis

While the results are robust to various fixed effects and radius of control regions, in this section, I provide three distinct sensitivity analyses for the baseline results.

Alternative Difference-in-Differences Methods. As discussed earlier in this section, researchers have introduced updated methods to estimate difference-in-differences regressions. I use Sun and Abraham (2021), Gardner (2021), and Callaway and Sant'Anna (2021) that primarily deal with staggered designs to check if the pre-event parallel trends and the post-event negative spillover effect still hold. Figure C.1 represents the point estimate of my baseline results with these three alternative methods.[23] The pre-event trend is very similar to Sun and Abraham (2021), and the other two show better parallel trends than the baseline method. Moreover, we can see that the decline in employment is persistent among all methods. Therefore, I can conclude that my results are robust to these alternative methods.

Alternative Identification. The main identification is centered around finding the best possible counterfactual to the event establishment. Here, I introduce an alternative approach in which the treatment regions are unchanged (i.e., 6km around the mass layoff establishment), but the control regions differ. For each event, the control region is a ring around the mass layoff establishment with a smaller radius of 15km and a larger radius of 20km. A 15km radius is chosen to minimize the potential spillover to the control area. To have a comparable control region, I use inverse propensity score weighting (IPW). The control is re-weighted

[23] Table C.1 represents the point estimates, standard errors, and significance of estimates. After the second year, all measures are statistically significant.

based on pre-event employment trends and industry (2-digit NAICS) composition. Figure C.2 displays the re-weighting method alongside the main identification. The parallel trends assumption holds even better for the alternative method, and in the post-event period, we see a similar trend with larger effects in years two and three. In the alternative method, the control regions are mostly within the same CZ as the event, suggesting that some workers get reemployed within the CZ.

Falsification Test. What if the drop in employment levels is not due to the mass layoff shock but is a local-specific decline in the economy? To address this concern, I use a falsification test. First, I randomly select a 10 percent sample from the main sample. Second, I define 100 similar studies to the main analysis. In each of these analyses, there are 132 events, and each fake event simulates one real event. Each fake event is drawn from a sample with the same year, the same industry (2-digit NAICS), and the same commuting zone as the real event. Third, I follow the same structure as the main identification to define treatment and control areas, and finally, I run equation (5) 100 times. Figure C.3 shows the visualization of the fake analysis in grey lines and the actual regression line in red. The pre-trend does not deviate from the simulation results, but the post-trend completely deviates from the simulation after the first year following the event.

5 Channels of Spillover Effects

In Section 2, the discussion revolved around four key channels of spillover effects on neighboring establishments: thick labor markets (or labor market pooling), knowledge sharing, input-output linkages, and local multipliers. In the subsequent section, I comprehensively examine these mechanisms, verifying their presence or absence with empirical evidence. Given these channels' complex and intertwined nature, it is not feasible, at least with the available data, to precisely decompose the magnitudes of each mechanism. Instead, the focus is on leveraging concepts and indexes established within the economic clustering literature to shed light on the importance and existence of these mechanisms.[24, 25]

5.1 Economies of Agglomeration Channels

Labor Market Pooling. Mass layoffs inherently lead to a direct reduction in the thickness of the local labor market. This contraction in the labor pool potentially impacts both the pace and quality of job matches within the region. To explore this hypothesis, I employ a data-driven approach by calculating the share of employment flow between industry pairs. The analysis is conducted at the 3-digit NAICS industry level, utilizing a 5 percent sample of employer-employee matched data from 2000 to 2019. First, I construct a sample of workers changing employers between years $t-1$ and t, and then I calculate the proportion of workers in industry i who move to industry j. A higher share of employment flow between industry pairs indicates a higher share of using the same labor pool between the industries. I categorize each combination of a mass layoff event and an affected establishment into three industry and skill proximity tiers based on the distribution of employment flow. These tiers are divided into industry pairs' lower, middle, and upper thirds.

Figure 12's top panel presents the outcomes of the difference-in-differences estimation (equation (4)), computed for three sub-samples ranked by their labor market pooling proximity. The findings indicate that establishments closer to the event regarding sharing the same labor market exhibit a more pronounced drop in employment. While the spillover effects are negative across all three groups, the spillover effect for the industries least related to each other is not statistically significant. In contrast, moderately and highly related industries demonstrate statistically significant spillover effects, and highly related industries experienced 28 percent more employment drop than moderately related industries. This observation supports the hypothesis that labor market pooling is a channel through which mass layoff events extend their impact to nearby establishments.

[24] See Delgado et al. (2012), Delgado et al. (2016), Ellison et al. (2010), Glaeser and Kerr (2009), Porter (2003), Duranton and Overman (2005).

[25] Delgado et al. (2016) and Delgado et al. (2012) provide a comprehensive overview of literature on economic closeness and clustering sectors, and I have used their definitions and insights extensively for this section.

Input-Output Linkages. Mass layoffs influence the input-output linkages within the local area, impacting upstream and downstream establishments. To quantitatively assess this channel of spillover, I turn to the widely used Benchmark Input-Output (I-O) accounts prepared by Bureau of Economic Analysis[26] which document the flow of intermediate goods and services between industry pairs. I leverage this data to quantify how mass layoffs influence these intricate inter-industry relationships.(Delgado et al., 2016). I follow Ellison et al. (2010) suggestion of creating a symmetric I-O index as follows:

$$IO_{ij} = Max[input_{i\rightarrow j}, input_{i\leftarrow j}, output_{i\rightarrow j}, output_{i\leftarrow j}], \tag{7}$$

where $input_{i\rightarrow j}$ is the share of industry i's total input value which is bought from industry j, and $output_{i\rightarrow j}$ is the share of industry i's total output value which is sold to industry j.

The I-O index serves as a metric for quantifying the linkages between two industries, capturing the extent of buying and selling activities between them. Ranging from zero to one, a value of zero indicates no transactions occurring between the two industries. As with the previous measures, the middle panel of Figure 12 displays the spillover effects categorized by the degree of linkage between the industries of the event establishment and affected establishments. The results highlight that industries with closer linkages experience more substantial employee losses. Among the three channels examined, input-output linkages yield the most robust and pronounced results, emphasizing the importance of I-O linkages.

Knowledge Spillover. Knowledge sharing among workers from different firms can occur through two primary pathways: formal and informal interactions between workers and workers' movement to new firms, facilitating knowledge exchange through interactions with new colleagues. While quantifying personal interactions among workers from different firms is not feasible within a quantitative framework, we can proxy potential knowledge spillover by comparing shared skills between industry pairs. Labor occupations have commonly served as a metric for assessing the degree of similarity in skills shared between various industries (Glaeser and Kerr 2009; Gabe and Abel 2011). In my analysis, I leverage data from the

[26] I use 2016 data at 3-digits NAICS from Bureau of Economic Analysis.

OES Survey conducted by the Bureau of Labor Statistics in 2016. This dataset encompasses occupations within the non-governmental sector and offers insights into the prevalence of each occupation within different industries at the 4-digit NAICS code. Specifically, for each occupation, OES provides the proportion of that occupation relative to the total occupational employment within the industry. Utilizing this dataset and following the approach outlined by Glaeser and Kerr (2009) and Delgado et al. (2016), I calculate the pairwise correlation between the occupational compositions of any two industries:

$$Occ_{ij} = Correlation(Occupation_i, Occupation_j), \tag{8}$$

where $Occupation_i$ is a vector of the share of occupations in industry i, a higher correlation indicates that the two industries share more skill sets. The top panel of Figure 12's bottom panel represents the results for sub-samples of labor occupation. Evidently, industries with a higher rate of shared occupation with the event industry lost more employment.

All three measures consistently suggest that industries that are economically closer experience more employment decline. Table 8 shows the correlation between each of these measures. While they are positively correlated, their weak correlations suggest that each of them mostly captures a different channel.

Finally, to summarize the agglomeration channels, I merge the measures that exhibited spillover effects - input-output linkages and employment flow to estimate comprehensive spillover impacts. The affected establishments are categorized into three groups based on their economic proximity to the event establishment: the least related (lowest 50 percent in both measures), modestly related (top 50 percent in one measure), and highly related (top 50 percent in both measures). The results in Table 6 reveal insignificant spillover effects for the least related industries; however, establishments with even moderate economic association, as indicated by either input-output linkages or industry transitions, exhibit significant negative spillover effects. This highlights the intricate nature of economic connections and their role in influencing the consequences of mass layoffs.

5.2 Tradability and Local Multiplier Effect

At a higher level of categorization, industries can be divided into two broad sectors: tradable and non-tradable. Tradable industries produce goods and services that can be sold in national or international markets and thus are not constrained by the local economy's market. Conversely, non-tradable industries rely on local market demand, as their products are not transferable to other markets. I segment the event and affected industries into tradable and non-tradable sectors, resulting in four sub-samples.[27] Table 7 presents the outcomes of equation (4) for them.

Column (1) displays the negative spillover effect of the tradable events on tradable industries. In this case, neither the event nor the affected establishments were limited to the local market. Hence, the demand for the affected establishments is maintained, and even if it is, they can sell their final products to new buyers outside of the local market. Therefore, the primary mechanism behind the 4.9 percentage points drop in employment of tradable establishments is the agglomeration economies, discussed in section 5.1.

Column (2) delves into the impact of tradable events on non-tradable establishments, showing 4.4 percentage points decline in non-tradable sector employment. Here, the local multiplier effect is a key channel driving the negative spillover. Given that the sectors of the event and affected establishments are different, the local multiplier effect is the substantial driver of the spillover effect. The decline in the number of workers reduces the demand for non-tradable goods and services and emerges as a decline in employment.

Column (3) presents the effect of non-tradable events on tradable establishments. The estimation is comparatively smaller than in Columns (1) and (2) by more than 35 percent, which could be attributed to two potential reasons. Firstly, compared to Column (1), economic closeness is weaker due to the establishments belonging to different sectors than the event. Secondly, unlike Column (2), the affected establishments are not reliant on local demand, causing the local multiplier effect to be less influential.

Lastly, in Column (4), I fail to reject the null hypothesis concerning the impact of non-tradable events on non-tradable establishments. While local multiplier effects and forces of

[27] I use Delgado et al. (2016) results to define tradable sectors. They use multiple measures of economic distance and choose 778 sectors (at 6-digit NAICS) as tradable sectors.

agglomeration economies push employment levels down, there is a positive channel at play as well. When both event and affected establishments are in non-tradable sectors, closure or downsizing of the event establishment opens up opportunities for competitors to fulfill the local demand. Therefore, establishments in the same industry will expand and hire more workers.

6 Conclusion

In this study, I leveraged extensive administrative data, including precise geographic coordinates of all establishments in California, to assess the spillover effects of large-scale mass layoffs on nearby establishments. My findings present compelling evidence that large mass layoffs cause a persistent, negative impact on nearby establishments' employment levels, with clear indications of spatial decay. Spillover effects diminish to insignificance beyond a 6 km radius of the event establishment. Within this 6 km radius, the average employment shock across 132 events is 5.5 percent, resulting in a 6 percentage point decline in employment four years later. In other words, a 1 percent employment shock caused 1.1 percentage point spillover effects on employment within 6km of the event. Moreover, treated areas experienced a 9.8 percentage point decline in total earnings and a 3 percentage point decline in the number of operating establishments. However, there is no tangible alteration in the average earnings per employee. For the first time in the literature, this paper explores and tests the importance of all three channels of agglomeration (labor market pooling, knowledge spillover, and input-output linkages) on spillover effects. I show that when the industry of event establishments and affected establishments are closer in terms of any of these agglomeration channels, the impact of mass layoffs on employment intensifies.

Furthermore, for the first time in the literature, I show the spillover effects of mass layoffs at the intensive margins by employing a balanced sample of surviving establishments after the events. At the intensive margins, employment levels of neighboring establishments decline by 2 percentage points four years later. Using the establishment level results, I also show heterogeneity in the effects of mass layoff by type of firm. Overall, establishments that belong to younger and smaller firms experience greater employment decline compared to their larger and older counterparts.

These findings can provide insights for policymakers seeking to respond optimally to large mass layoffs. Policymakers can use QCEW datasets to identify and target potentially affected nearby establishments by distance. Moreover, adopting a more targeted approach by focusing on younger and smaller establishments, as well as those economically closer to the event establishment, may prove effective in mitigating the adverse effects of mass layoffs.

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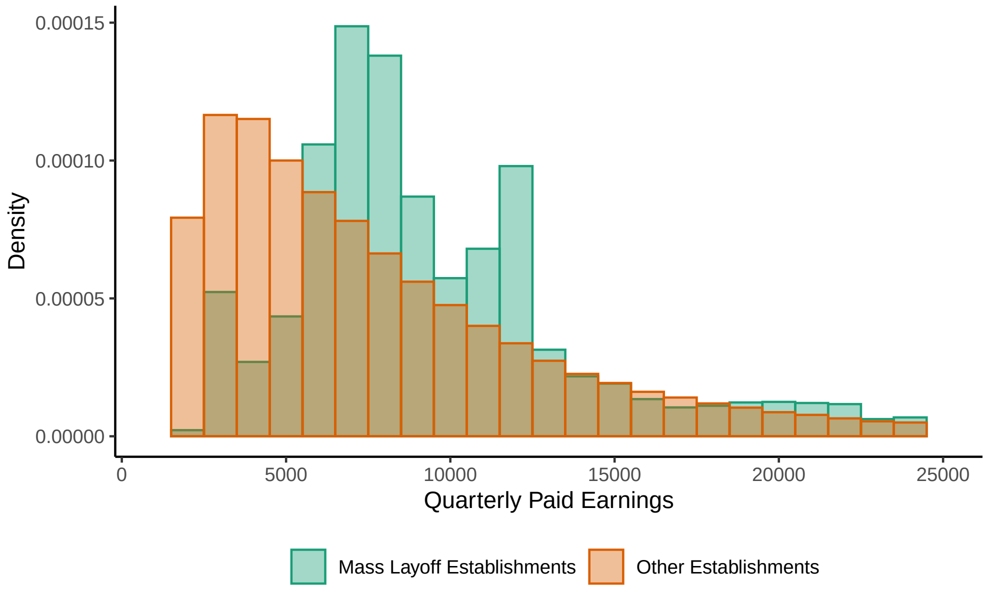
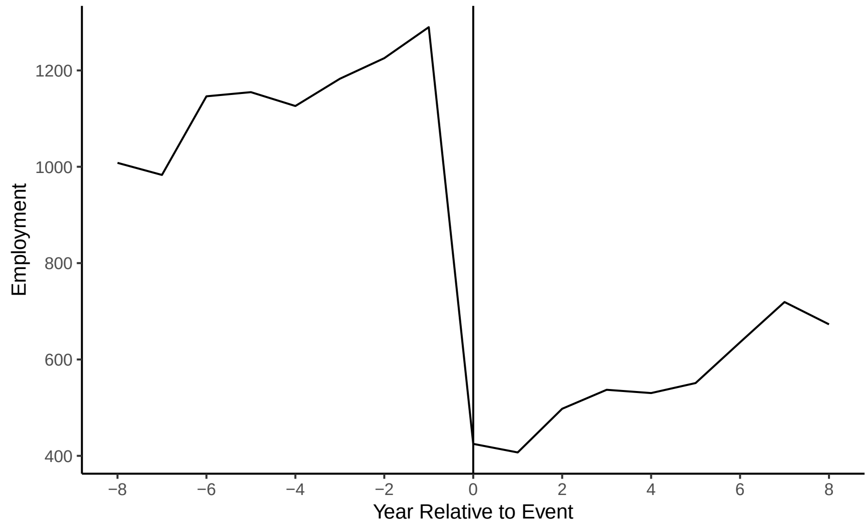
Figure 1: Distribution of Average Quarterly Earnings in 2003

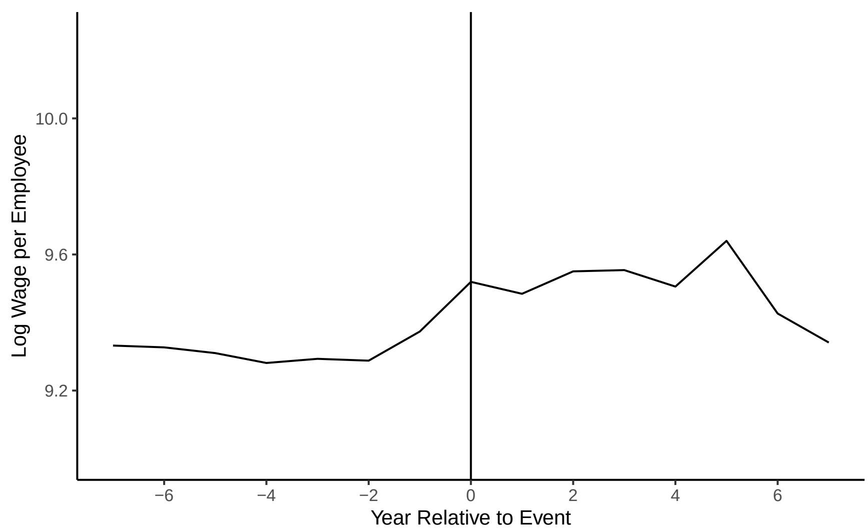


Note: This figure shows the average quarterly paid earnings distribution at the establishment level for firms associated with mass layoff and non-mass layoff establishments in 2003. Earnings include both part-time and full-time pays. The mass layoff establishment sample includes all establishments of firms with at least one mass layoff establishment in 2004-2015. A mass layoff is defined as 30 percent decline in employment and a reduction of 500 employees within a year.

Figure 2: Mass Layoff Establishments Over Time



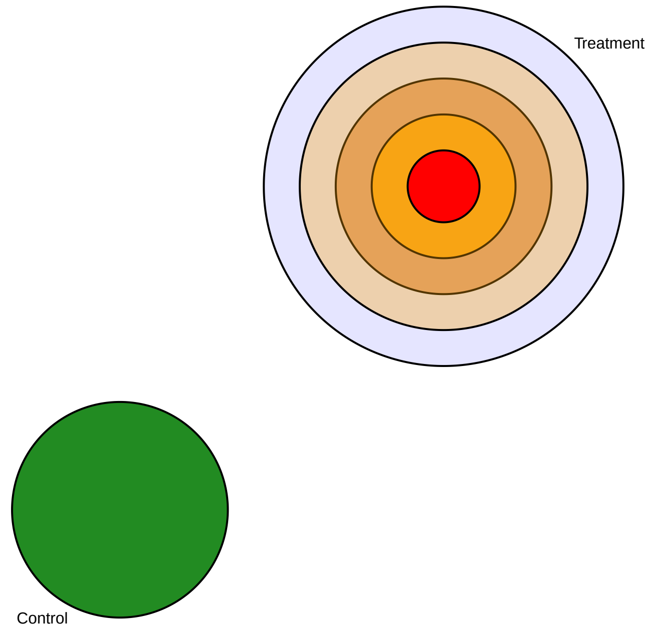
(a) Employment Level



(b) Average Quarterly Earnings per Employee

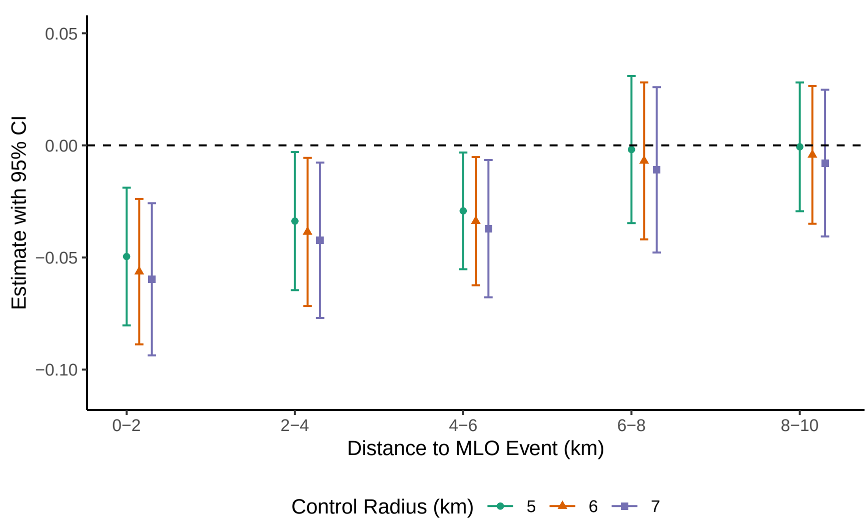
Note: Panel (a) shows the annual employment level of mass layoff establishments conditional on being operational. Panel (b) shows the log mean of quarterly earnings per employee of mass layoff establishments conditional on being operational. In both panels, the sample is an unbalanced panel data, in which closed establishments are dropped.

Figure 3: Schematic of Treatment and Control Areas for Spatial Decay Analysis



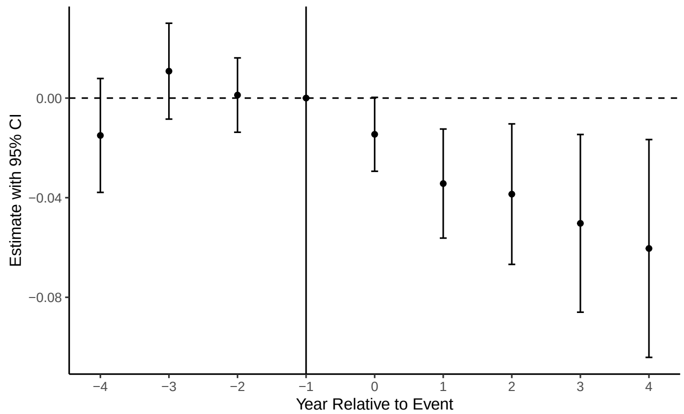
Note: This figure represents the schematic of treatment and control areas for spatial decay analysis. There are five treatment regions in the shape of sequential 2km donuts around the event establishment. The control area is a circle around the counterfactual establishment that can take radii of 5, 6, and 7km.

Figure 4: Spatial Decay in Employment Spillover Effects of Mass Layoffs

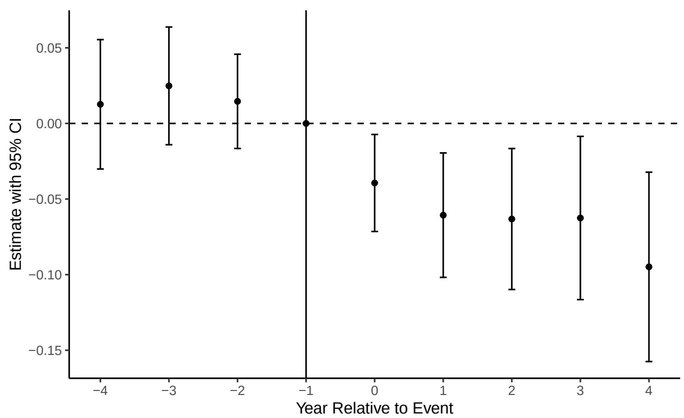


Note: This figure represents the results of equation (4) for various rings with radii varying by 2km and different circles radii. Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

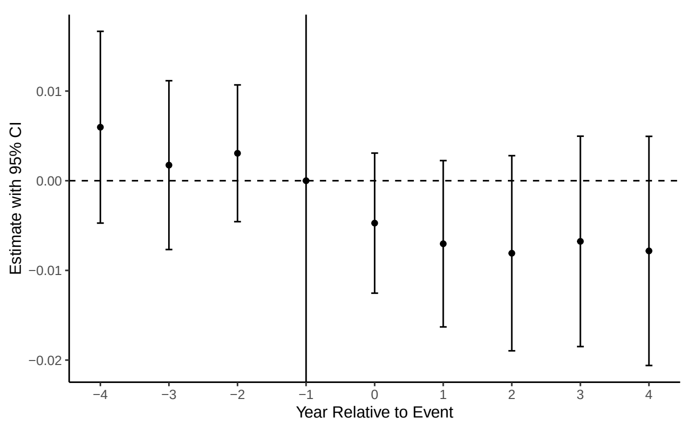
Figure 5: Spillover Effects of Mass Layoffs



(a) Employment



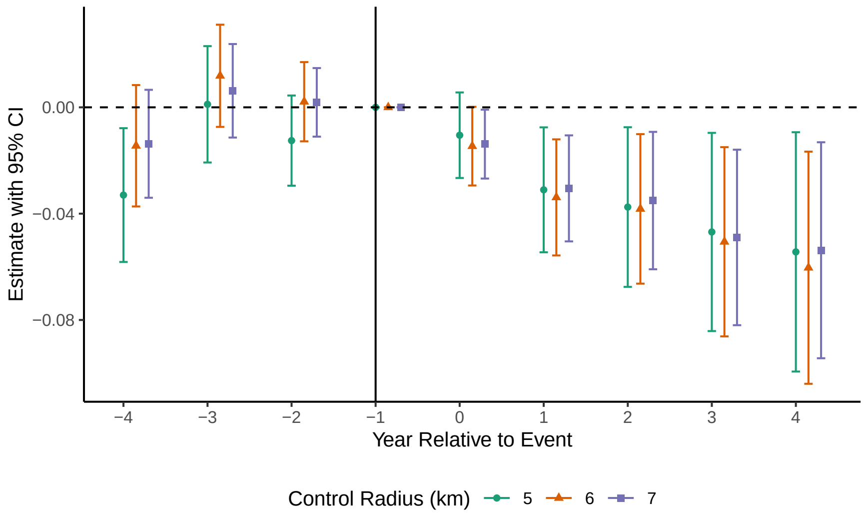
(b) Total Paid Earnings



(c) Earnings per Employee

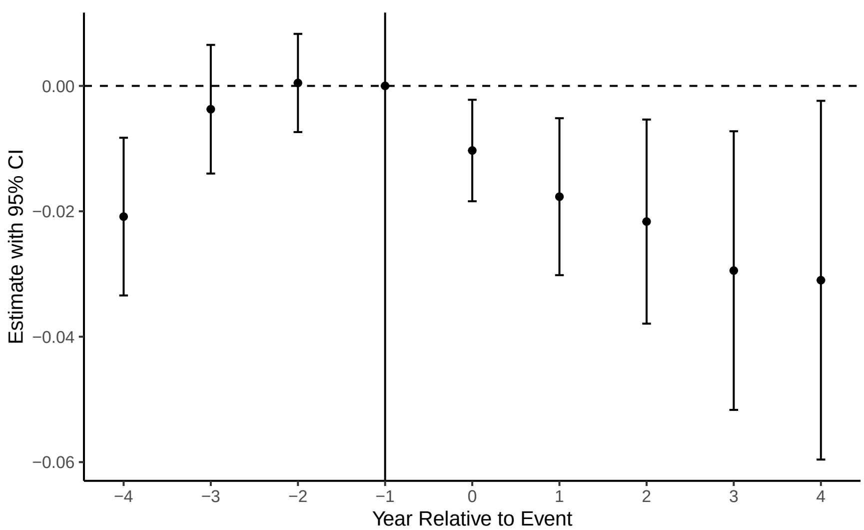
Note: This figure represents the results of equation (5) for log(employment), log(total paid earnings), and log(earnings per employee). Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Figure 6: Employment Spillover Effects by Various Control Radii



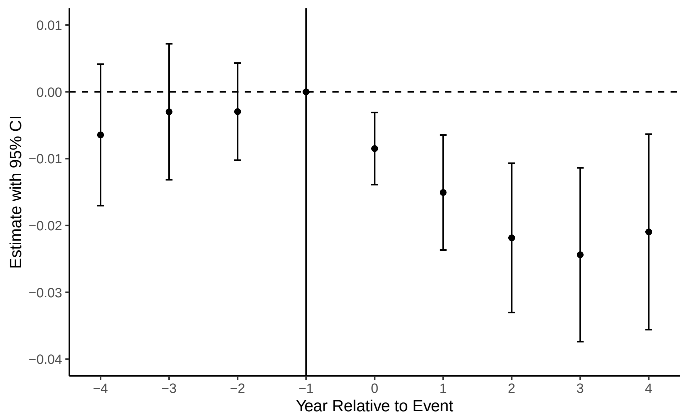
Note: This figure represents the results of equation (5) for log(number employment) using 3 different radii for control regions, while keeping the treatment radius at 6km. It suggests that the results are robust to changing size of control regions. The standard errors are clustered at the region level.

Figure 7: Spillover Effects on The Number of Operating Establishments

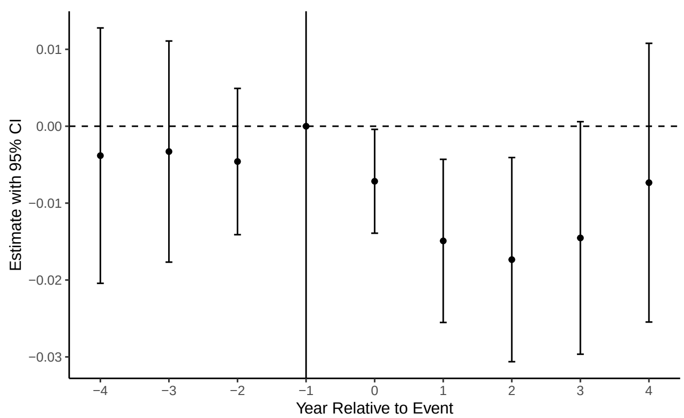


Note: This figure represents the results of equation (5) for log(number of establishments). I control for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

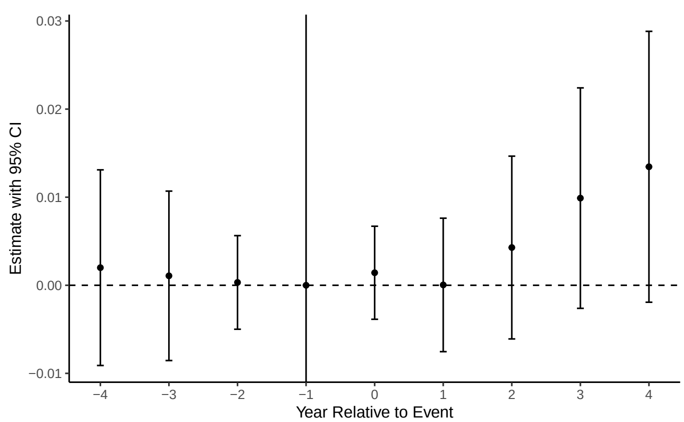
Figure 8: Spillover Effects of Mass Layoffs at Establishment Level



(a) Employment



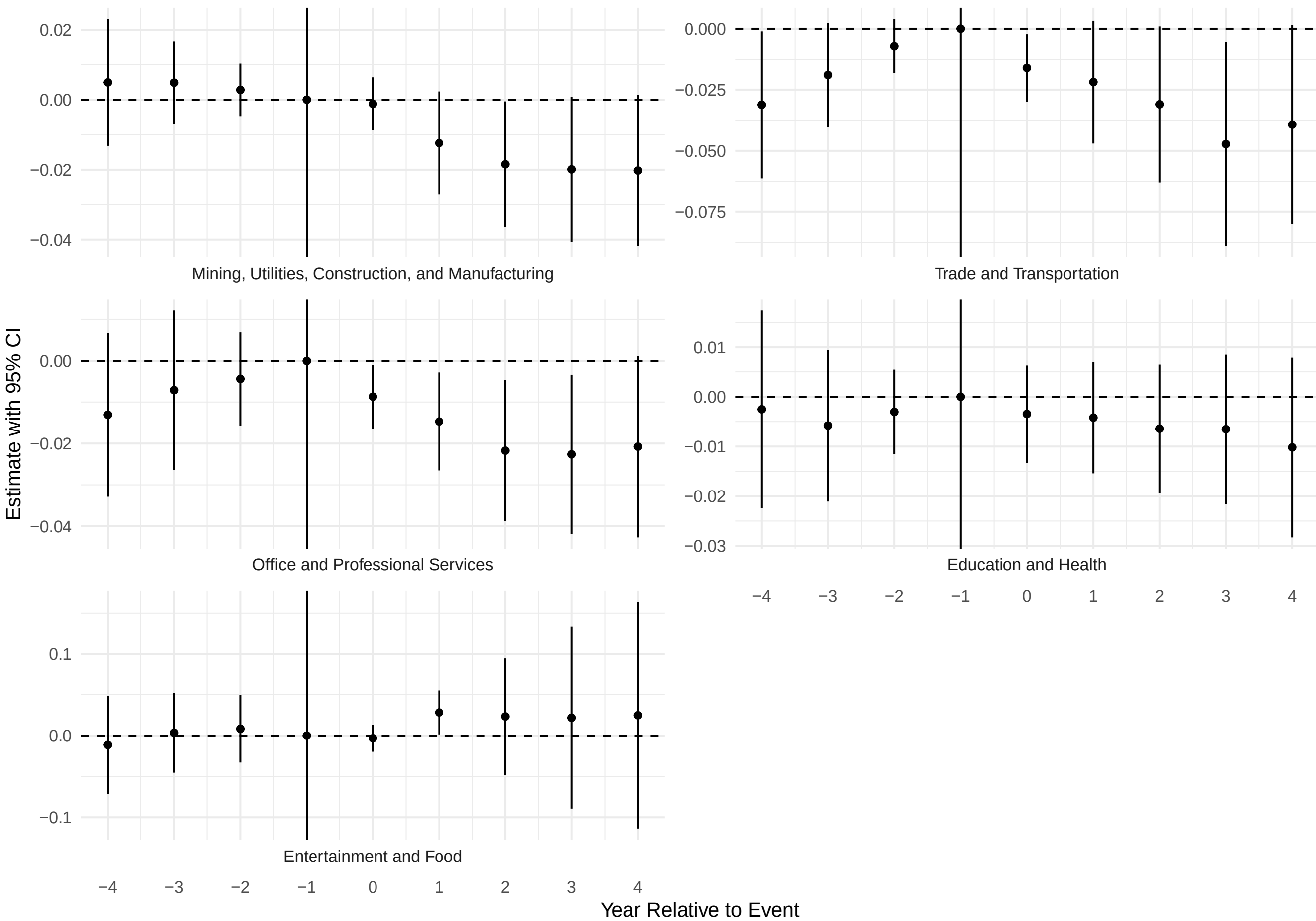
(b) Total Paid Earnings



(c) Earnings per Employee

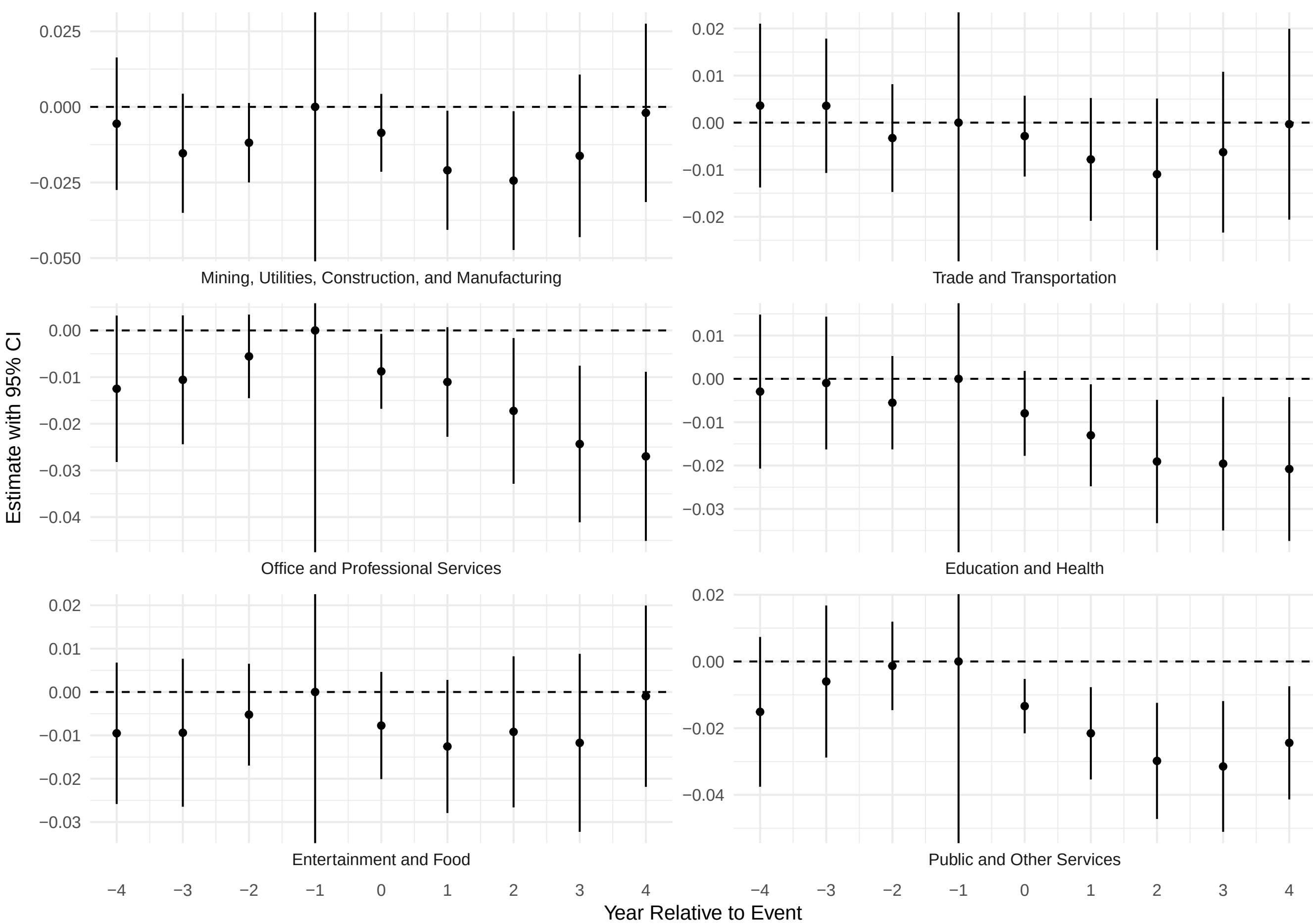
Note: This figure represents the results of equation (6) for log(employment), log(total paid earnings), and log(earnings per employee). Each regression controls for establishment ID, region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Figure 9: Employment Spillover Effects by Industry of Event Establishments



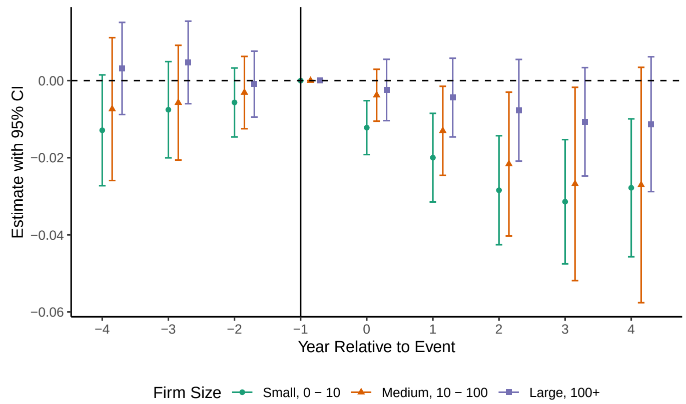
Note: This figure represents the results of equation (5) for log(employment) for 5 sub-samples divided by the industry of mass layoff establishments. Each regression controls for establishment ID, region, year, relative time, and industry fixed effects. The standard errors are clustered at the the region level.

Figure 10: Employment Spillover Effects by Industry of Affected Establishments

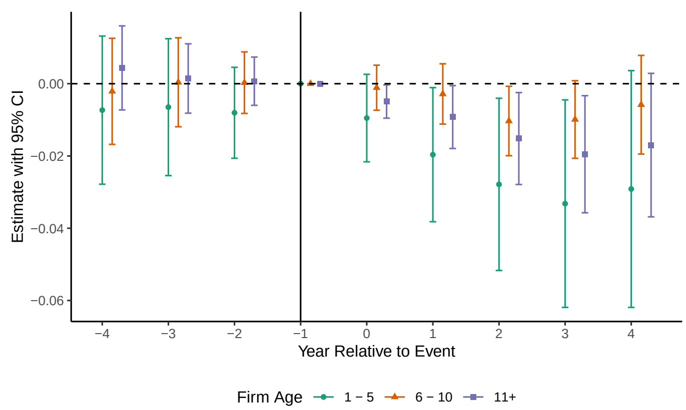


Note: This figure represents the results of equation (5) for log(employment) for 6 sub-samples divided by the industry of affected establishments. Each regression controls for establishment ID, region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

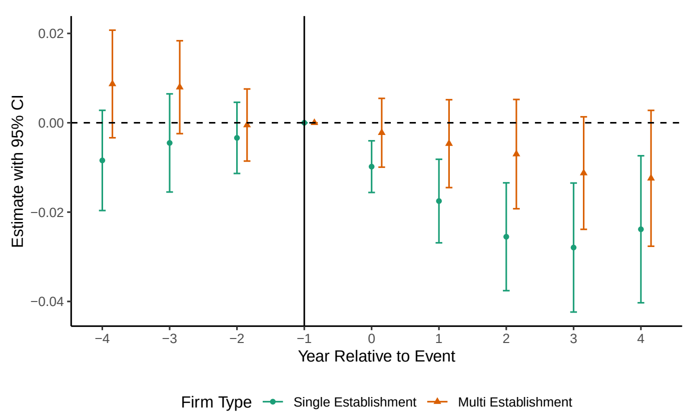
Figure 11: Employment Spillover Effects by Firm Type



(a) Firm Size



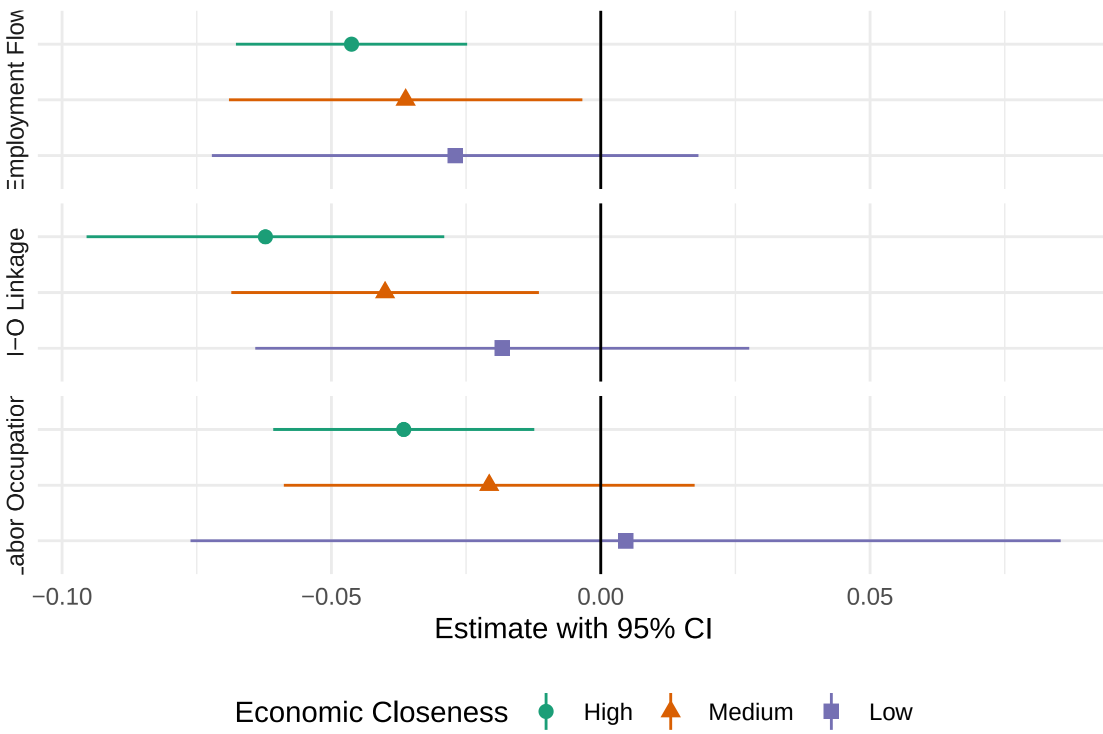
(b) Firm Age



(c) Firm Type

Note: This figure represents the results of equation (6) for log(employment). Each panel shows the employment effects by type of establishment. Each regression controls for establishment ID, region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Figure 12: Employment Spillover Effects by Economic Closeness



Note: This figure represents the results of equation (4) for log(employment). Each panel shows three regression analysis for sub-samples divided by economic closeness indexes. Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at region Industry level.

Table 1: Industries of Mass Layoff Establishments

Industry	Number of Mass Layoff Events
Professional and Business Services	27
Finance and Insurance	23
Educational and Health Services	22
Manufacturing	17
Trade, Transportation and Utilities	15
Construction	12
Information	10
Other Sectors	6
Total	132

Note: This table shows the industry of the mass layoff events using QCEW administrative data. A mass layoff is defined as 30 percent decline in employment and a reduction of 500 employees within a year. The industry breakdown is based on super sectors defined by the Bureau of Labor Statistics (BLS), which combines some of the 2-digits NAICS codes. Trade, Transportation, and Utilities is 22, 42, 44, 45, 48, and 49; Financial Activities is 52 and 53; Professional and Business Services is 54, 55, and 56; Educational and Health Services is 61 and 62. Other Sectors are combination of different NAICS codes that are suppressed within one group.

Table 2: Summary Statistics for Establishments Within Treatment and Control Regions

	Control	Treatment	Difference
Employment	14.9	16.78	1.82
	(0.97)	(0.72)	(1.19)
Quarterly Earnings	10594.42	9870.53	-721.09
	(709.53)	(281.92)	(768.28)
Firm Age	8.32	8.81	0.49***
	(0.28)	(0.13)	(0.3)

Note: This table shows the mean of employment level and quarterly earnings of event establishments and age of firms associated with the event establishments using QCEW administrative data (standard deviations in parentheses). Treatment and control areas are defined as 6km around the event and counterfactual establishments. All means are calculated at one year before the event year.

Table 3: Industry Share of Treatment and Control Regions

	Control	Treatment	Difference
Natural Resources and Mining	0.01	0.01	0.00
	(0.00)	(0.00)	(0.00)
Trade, Transportation and Utilities	0.15	0.15	0.01
	(0.01)	(0.00)	(0.01)
Construction	0.06	0.05	0.00
	(0.00)	(0.00)	(0.01)
Manufacturing	0.05	0.05	0.00
	(0.00)	(0.00)	(0.01)
Information	0.04	0.02	-0.02
	(0.01)	(0.00)	(0.01)
Financial Activities	0.08	0.08	0.00
	(0.00)	(0.00)	(0.01)
Professional and Business Services	0.14	0.14	0.01
	(0.01)	(0.01)	(0.01)
Educational and Health Services	0.12	0.12	0.01
	(0.01)	(0.01)	(0.01)
Leisure and Hospitality	0.07	0.07	0.00
	(0.00)	(0.00)	(0.00)
Other Services (Except Public Admin.)	0.25	0.27	0.03
	(0.02)	(0.01)	(0.02)
Public Administration	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Unknown	0.05	0.03	-0.02
	(0.01)	(0.00)	(0.01)

Note: This table shows the industry of the treatment and control areas using QCEW administrative data. Treatment and control areas are defined as 6km around the event and counterfactual establishments. The industry breakdown is based on super sectors defined by the Bureau of Labor Statistics (BLS), which combines some of the 2-digits NAICS codes. Natural Resources and Mining is NAICS codes 11 and 21; Trade, Transportation, and Utilities is 22, 42, 44, 45, 48, and 49; Financial Activities is 52 and 53; Professional and Business Services is 54, 55, and 56; Educational and Health Services is 61 and 62; Leisure and Hospitality is 71 and 72.

Table 4: Baseline Results for Spillover Effect of Mass Layoffs

Dependent Variables:	Employment				Total Earnings Paid				Earnings per Employee			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
τ = -4	-0.0150	-0.0130	-0.0184	-0.0085	0.0126	-0.0201	0.0081	0.0221	0.0060	0.0025	0.0056	0.0081
	(0.0117)	(0.0117)	(0.0119)	(0.0116)	(0.0218)	(0.0214)	(0.0220)	(0.0221)	(0.0055)	(0.0051)	(0.0054)	(0.0058)
τ = -3	0.0108	0.0151	0.0079	0.0133	0.0249	0.0161	0.0210	0.0307	0.0017	-0.0001	0.0013	0.0035
	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0198)	(0.0192)	(0.0197)	(0.0201)	(0.0048)	(0.0045)	(0.0047)	(0.0051)
τ = -2	0.0012	0.0041	-0.0014	0.0015	0.0146	0.0131	0.0108	0.0173	0.0031	0.0030	0.0023	0.0046
	(0.0076)	(0.0073)	(0.0077)	(0.0076)	(0.0159)	(0.0153)	(0.0157)	(0.0160)	(0.0039)	(0.0037)	(0.0038)	(0.0040)
τ = -1												
τ = 0	-0.0146*	-0.0208***	-0.0128*	-0.0114	-0.0394**	-0.0419***	-0.0393**	-0.0348**	-0.0047	-0.0030	-0.0058	-0.0037
	(0.0076)	(0.0075)	(0.0076)	(0.0076)	(0.0164)	(0.0154)	(0.0163)	(0.0165)	(0.0040)	(0.0037)	(0.0040)	(0.0042)
τ = 1	-0.0343***	-0.0417***	-0.0301***	-0.0293***	-0.0607***	-0.0603***	-0.0572***	-0.0524**	-0.0070	-0.0062	-0.0085*	-0.0046
	(0.0112)	(0.0114)	(0.0111)	(0.0110)	(0.0210)	(0.0200)	(0.0210)	(0.0211)	(0.0047)	(0.0044)	(0.0047)	(0.0050)
τ = 2	-0.0386***	-0.0437***	-0.0331**	-0.0310**	-0.0632***	-0.0528**	-0.0590**	-0.0515**	-0.0081	-0.0082	-0.0093*	-0.0049
	(0.0144)	(0.0149)	(0.0143)	(0.0138)	(0.0238)	(0.0232)	(0.0237)	(0.0234)	(0.0055)	(0.0051)	(0.0055)	(0.0058)
τ = 3	-0.0503***	-0.0511***	-0.0445**	-0.0360**	-0.0625**	-0.0454*	-0.0585**	-0.0425	-0.0068	-0.0074	-0.0091	-0.0028
	(0.0182)	(0.0187)	(0.0181)	(0.0171)	(0.0275)	(0.0273)	(0.0276)	(0.0265)	(0.0060)	(0.0055)	(0.0060)	(0.0063)
τ = 4	-0.0604***	-0.0528**	-0.0570***	-0.0418**	-0.0949***	-0.0625**	-0.0922***	-0.0682**	-0.0078	-0.0084	-0.0096	-0.0021
	(0.0223)	(0.0226)	(0.0220)	(0.0206)	(0.0319)	(0.0316)	(0.0318)	(0.0303)	(0.0065)	(0.0060)	(0.0065)	(0.0069)
Fixed-effects												
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relative Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (4-digit)	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Region × Industry		Yes				Yes				Yes		
Calendar Year × Industry			Yes				Yes				Yes	
Fit statistics												
Observations	738,479	738,479	738,479	738,479	738,479	738,479	738,479	738,479	712,594	712,594	712,594	712,594
R^2	0.28089	0.55212	0.29100	0.10272	0.21514	0.46773	0.22570	0.09138	0.34184	0.55581	0.35069	0.06325

Clustered (Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The dependent variables for columns (1)-(4) is log(employment), for (5)-(8) is log(total paid earnings), and for (9)-(12) is log(earnings per employee).Columns (1), (5), and (9) are the baseline results presented in Figure 5. In columns (2), (6), and (10), the interaction of region and industry are included. In columns (3), (7), and (11), interaction of year and industry are included. In columns (4), (8), and (12), no industry or interaction with industry is included.

Table 5: Spillover Effect of Mass Layoffs on Surviving Establishments

Dependent Variables:	Employment		Total Paid Earnings		Earnings per Employee	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
τ = -4	-0.0109*	-0.0064	-0.0115	-0.0038	-0.0008	0.0020
	(0.0065)	(0.0054)	(0.0103)	(0.0084)	(0.0053)	(0.0056)
τ = -3	-0.0065	-0.0030	-0.0112	-0.0033	-0.0027	0.0011
	(0.0058)	(0.0052)	(0.0084)	(0.0073)	(0.0044)	(0.0049)
τ = -2	-0.0036	-0.0030	-0.0080	-0.0046	-0.0021	0.0003
	(0.0035)	(0.0037)	(0.0051)	(0.0048)	(0.0029)	(0.0027)
τ = -1						
τ = 0	-0.0080***	-0.0085***	-0.0068*	-0.0072**	0.0013	0.0014
	(0.0026)	(0.0027)	(0.0035)	(0.0034)	(0.0027)	(0.0027)
τ = 1	-0.0144***	-0.0151***	-0.0142***	-0.0149***	0.0002	0.0000
	(0.0042)	(0.0044)	(0.0052)	(0.0054)	(0.0039)	(0.0038)
τ = 2	-0.0212***	-0.0219***	-0.0167**	-0.0174**	0.0043	0.0043
	(0.0056)	(0.0057)	(0.0068)	(0.0067)	(0.0053)	(0.0053)
τ = 3	-0.0237***	-0.0244***	-0.0136*	-0.0145*	0.0101	0.0099
	(0.0066)	(0.0066)	(0.0080)	(0.0077)	(0.0065)	(0.0064)
τ = 4	-0.0207***	-0.0210***	-0.0072	-0.0073	0.0133*	0.0134*
	(0.0074)	(0.0074)	(0.0096)	(0.0092)	(0.0080)	(0.0078)
Fixed-effects						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Relative Time	Yes	Yes	Yes	Yes	Yes	Yes
Establishment ID	Yes	Yes	Yes	Yes	Yes	Yes
Industry (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size		Yes		Yes		Yes
Firm Age		Yes		Yes		Yes
Fit statistics						
Observations	3,461,875	3,359,846	3,508,932	3,397,618	3,461,096	3,359,120
R^2	0.95119	0.95364	0.95988	0.96212	0.92094	0.92329

Clustered (Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The dependent variable for columns (1) and (2) is log(employment), for (3) and (4) is log(total paid earnings), and for (5) and (6) is log(earnings per employee). This table displays the results of equation (6) with two different sets of controls. Columns (1), (3), and (5) follow the baseline controls, but in columns (2), (4), and (6), firm size and firm age controls are included; however, the results are robust to control changes.

Table 6: Spillover Effects of Mass Layoffs by Economic Closeness Based on I-O linkages and Employment Flow

Dependent Variable:	Employment		
Model:	(1)	(2)	(3)
ML × Post Event	0.0025	-0.0546***	-0.0574***
	(0.0114)	(0.0126)	(0.0199)
Fixed-effects			
Region	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Calendar Year	Yes	Yes	Yes
Relative Time	Yes	Yes	Yes
Fit statistics			
Observations	198,472	272,447	258,000
R^2	0.42751	0.39886	0.46170

Clustered (Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table presents the results of equation (4) for three different subsamples from the main sample based on the economic closeness of affected establishments to the event establishment. The dependent variable is log(employment). Two measures are used in this table: employment flow and input-output linkages, and industry pairs are divided into the top and bottom 50 percent of the distribution of each measure. Column (1) sample is a set of establishments at the bottom half of both measures' distribution. In column (2) sample, affected establishments are at the top half of distribution in one of the measures. Finally, in column (3), affected establishments are at the top half of both measures.

Table 7: Spillover Effects of Mass Layoffs by Tradability of Event and Affected Establishments

Dependent Variable:	Employment			
Model:	Traded on Traded	Traded on Non-Traded	Non-traded on Traded	Non-traded on Non-Traded
ML × Post Event	-0.0487***	-0.0435**	-0.0280**	-0.0484
	(0.0124)	(0.0156)	(0.0134)	(0.0376)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Relative Time	Yes	Yes	Yes	Yes
Calendar Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	241,795	193,337	173,057	120,147
R^2	0.49657	0.29148	0.50889	0.30072

Clustered (Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This figure presents the results of equation (4) for four different subsamples from the main sample based on the tradability of the event and affected establishments' industry. The dependent variable is log(employment). To determine industries' tradability, I use Delgado et al. 2016 in which 778 6-digit NAICS codes are categorized as tradable industries.

Table 8: Correlation Between Economic Distance Indexes

Index	Employment Flow	I-O	Labor Occupation
Employment Flow	1		
I-O	0.11	1	
Labor Occupation	0.22	0.34	1

Appendix

A Relationship Between Local Economic Conditions and Mass layoff Incidence

To estimate the relationship between local labor market conditions and the probability of mass layoff events, I use two measures of GDP growth and employment growth at two different levels: year-industry (2-digits NAICS) and year-commuting zone-industry (1-digit NAICS) level. The result is four datasets that measure economic health at the industry and local-industry levels. Finally, I add the number of mass layoff incidences (132 total) to the related cells of each dataset. For the employment growth rate, I use QCEW data, and for the GDP growth rate, I use Bureau of Economic Analysis (BEA) data on industry and industry-county GDP. BEA estimates GDP at county, industry, and county-industry levels since 2001. The time period of these datasets is 2004-2015, the same period that we measure mass layoff events.

I use the following regressions to investigate if the decline in local economic conditions can predict large mass layoff events:

$$ML\ Incidence_{it} = \beta X_{it} + \epsilon_{it} \tag{9}$$

$$ML\ Incidence_{irt} = \beta X_{irt} + \epsilon_{irt} \tag{10}$$

X represents negative GDP growth or employment growth at the industry or CZ-industry level. Table A.1 represents the four estimates of 9 and 10. The only measure that shows a weak correlation is the GDP growth at the industry level. In contrast, the other measures suggest no correlation between the number of mass layoff incidences and economic conditions.

Table A.1: Relationship Between Economic Conditions and Number of Mass Layoff Incidences

Dependent Variable:	Mass Layoff Incidence	
Model:	Industry	CZ-Industry
Panel (a)		
-1 $\times$*Employment Growth Rate*	0.0175*	0.0001
	(0.0100)	(0.0005)
R^2	0.18866	0.03607
Panel (b)		
-1 $\times$*GDP Growth Rate*	0.0138	0.0000
	(0.0109)	(0.0001)
R^2	0.18752	0.03607
Observations	228	1,728

Clustered (Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Directly Displaced Workers

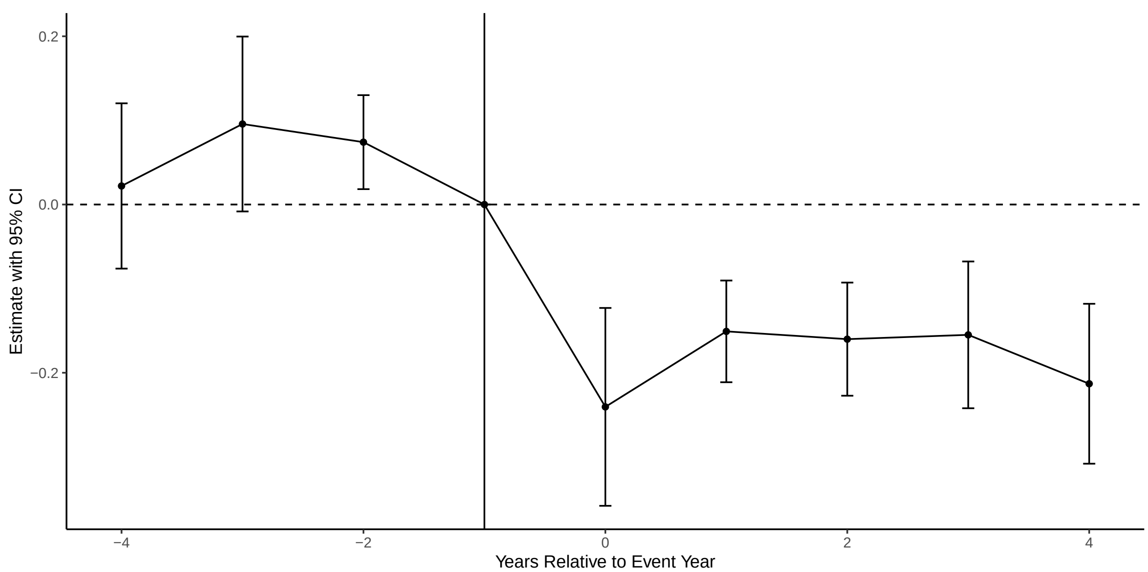
The focus of this paper is spillover effects of mass layoffs on nearby establishments. But, what are the labor market outcomes of the directly displaced workers from the event establishment? What are their chances to reach their pre-displacement earnings? To answer this, I employ a modify version of equation (5) at an individual level rather than a regional level for workers from 54 single establishment events:[28]

$$Y_{i\tau t} = \sum_{\tau=-4}^{-2} \alpha_\tau Event_{r\tau,t} + \sum_{\tau=0}^{4} \beta_\tau Event_{r\tau t} + \mu_i + \gamma_t + \lambda_\tau + \epsilon_{ir\tau t}, \tag{11}$$

where, $Y_{i\tau t}$ is displaced worker i's log of earnings, and I control for individual (μ_i), year (γ_t), and relative time (λ_τ) fixed effects. I cluster the standard errors at year level.

The results are displayed in Figure B.1, suggesting persistent income loss four years after the event, consistent with the displacement literature.

Figure B.1: Earnings of Displaced Workers Before and After Mass Layoff

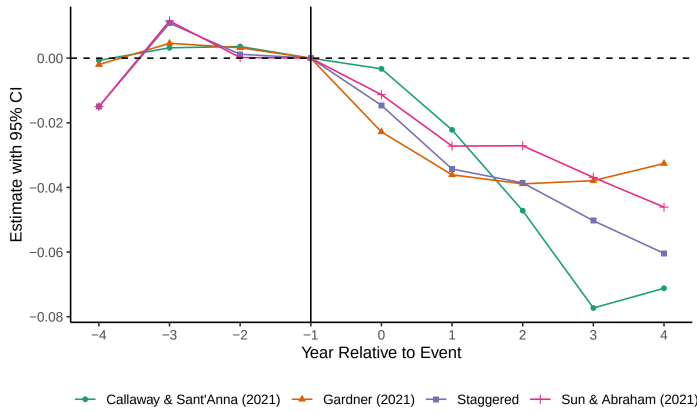


Note: The direct effect of mass layoffs on the earnings of displaced workers. The figure shows a difference-in-difference event study estimate for annual earnings of directly displaced workers using equation (11). The control group includes non-displaced workers in firms with at least 500 employees one year before the event. The standard errors are clustered at the year level. Individual, industry, calendar year, and relative year fixed effects are included. In order to be able to match event establishments with employer-employee matched data, Events are limited to single establishment cases.

[28]As explained in Data section, Quarterly Earnings (QE) are not at the establishment level but firm level. Therefore, I can only directly find the earnings of the single establishment events.

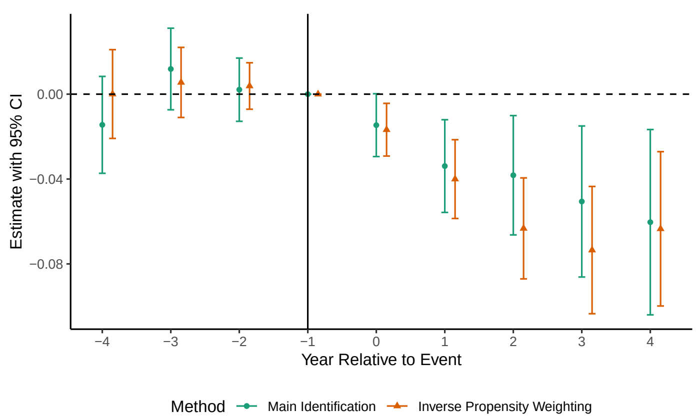
C Sensitivity and Robustness Checks

Figure C.1: Employment Spillover Effects by Various Difference-in-differences Methods



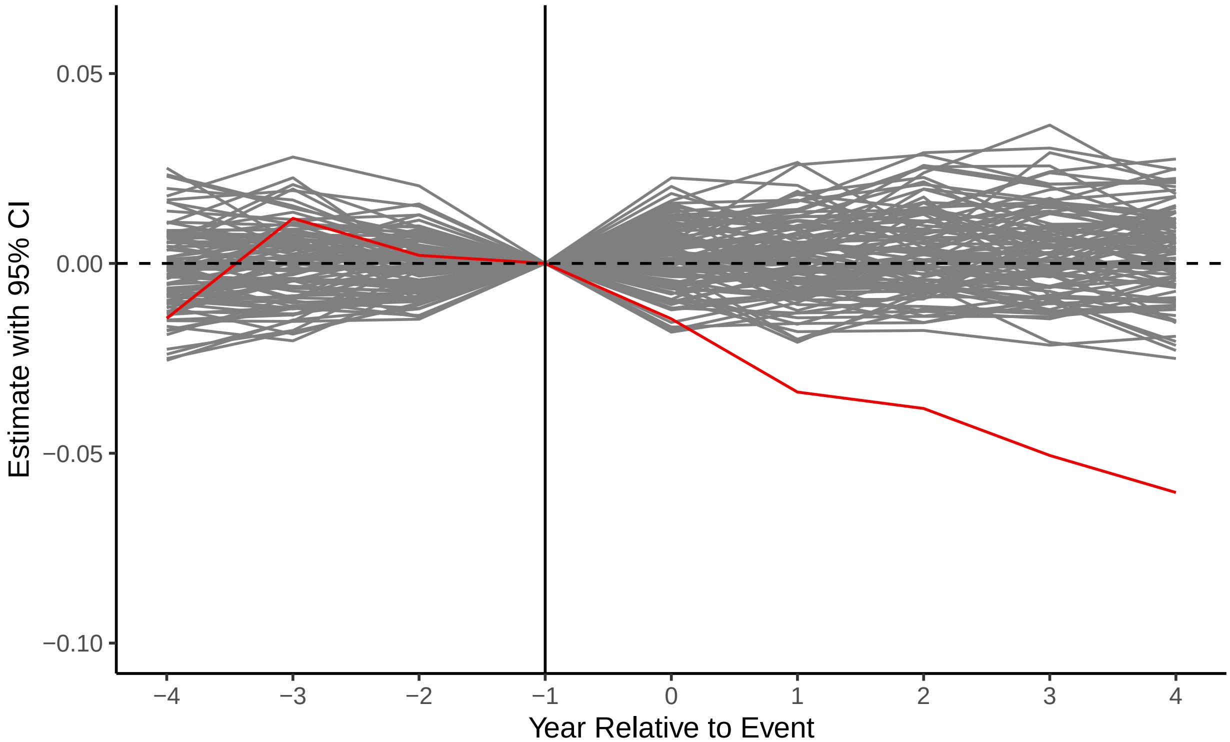
Note: This figure represents the results of equation (5) for log(employment), and compare it with proposed methods by Callaway and Sant'Anna (2021), Gardner (2021), and Sun and Abraham (2021). Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Figure C.2: Comparison Between Main and Alternative Identification



Note: This figure represents the results of equation (5) for log(employment), and compare it with the alternative method in section 4.3 in which the control region is a ring (15-20km) around the event, and it is re weighted using inverse propensity weighting method. Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Figure C.3: Placebo Regressions vs. Baseline Regression



Note: This figure represents the results of equation (5) for log(employment) (red line), and compare it with 100 regressions on randomly selected fake events (gray lines). Each regression controls for region, year, relative time, and industry fixed effects. The standard errors are clustered at the region level.

Table C.1: Baseline Results by Various Difference-in-differences Methods

Dependent Variables:	Employment			
Model:	(1)	(2)	(3)	(4)
τ = -4	-0.0007	-0.0020	-0.0150	-0.0150
	(0.0201)	(0.0029)	(0.0117)	(0.0117)
τ = -3	0.0032	0.0046*	0.0115	0.0108
	(0.0188)	(0.0020)	(0.0099)	(0.0098)
τ = -2	0.0036	0.0030	0.0002	0.0012
	(0.0197)	(0.0020)	(0.0075)	(0.0076)
τ = -1				
τ = 0	-0.0033	-0.0228***	-0.0113	-0.0146*
	(0.0186)	(0.0048)	(0.0073)	(0.0076)
τ = 1	-0.0222	-0.0361***	-0.0272***	-0.0343***
	(0.0191)	(0.0072)	(0.0100)	(0.0112)
τ = 2	-0.0472**	-0.0389***	-0.0271**	-0.0386***
	(0.0198)	(0.0097)	(0.0123)	(0.0144)
τ = 3	-0.0773***	-0.0379***	-0.0369**	-0.0503***
	(0.0184)	(0.0121)	(0.0159)	(0.0182)
τ = 4	-0.0712**	-0.0326**	-0.0461**	-0.0604***
	(0.0206)	(0.0148)	(0.0188)	(0.0223)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
Calendar Year	Yes	Yes	Yes	Yes
Relative Time	Yes	Yes	Yes	Yes
Industry (4-digit)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	738,479	738,479	738,479	738,479

Clustered (Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table presents the results of equation (5) for three different alternative methods dealing with staggered difference-in-differences and comparing it with the main identification. The visual representation of point estimates is in Figure C.1. The dependent variable is log(employment). Column (1) follows Gardner (2021), column (2) follows Callaway and Sant'Anna (2021), and column (3) follows Sun and Abraham (2021). Column (4) is the main identification result.

D Discussion on Spillover Effects on Housing Prices

The main focus of this paper is on studying the neighboring firms to large mass layoffs. However, the spillover effects are not limited to labor market. The people who live close-by and not necessarily work in the same area might also be affected by such a local economic shock.

One way of examining the potential effects on neighboring residents, is by estimating changes of housing prices. Housing is not just a consumption good, it is also a mean of accumulating wealth or speculation for housholds (Gao et al. 2020).

To estimate the spillover effect on housing prices, I utilize a recent dataset introduced by Contat and Larson (2022). This dataset id a balanced panel of annual housing price indexes (HPI) for single-family homes covering this study's time period. I also, use the census tract centroids from US Census Bureau to measure the spatial distance between tratcs. I use a similar approach to the alternative identification in section 4.3. The treatment area includes all census tracts which their centroids lie within 6km of the centroid of the mass layoff establishment's tract. The control area is all tracts within a 20km to 50km ring around the centroid of mass layoff establishment's tract. Finally, I reweight the control using inverse propensity weighting based on trend of pre event HPI, and estimate a modified version of equation (5):

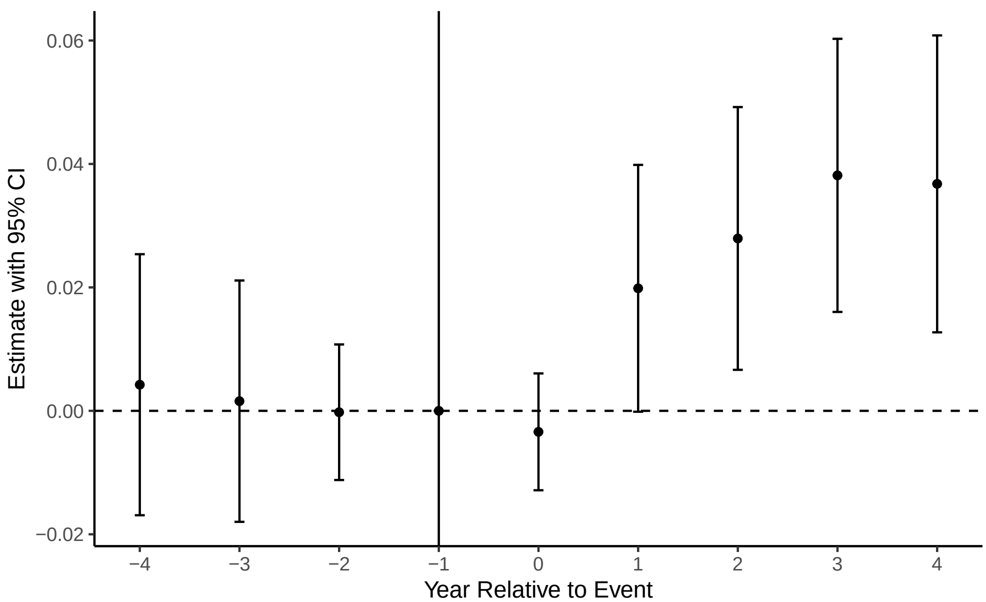
$$Y_{c\tau t} = \sum_{\tau=-4}^{-2} \alpha_\tau Event_{c\tau t} + \sum_{\tau=0}^{4} \beta_\tau Event_{c\tau t} + \gamma_t + \delta_c + \lambda_\tau + \epsilon_{ir\tau t}, \tag{12}$$

where $Y_{c\tau t}$ is HPI of census tract c at year t and relative time τ. I include census tract along with time fixed effects, and cluster standard errors at region[29] level.

Figure D.1 represents the event study results, indicating increase in housing prices in census tracts within 6km of the event census tract. It requires more research in the future to understand the mechanisms behind the changes in housing prices. However, the results suggest that home owners near large mass layoff events benefit from them, suggesting that plant closures or substantial decrease in economic activity near residential areas increase desirability.

[29] Region here is a treatment and control area pair.

Figure D.1: Spillover Effects of Mass Layoffs on HPI



Note: This figure represents the results of equation (12) for log(HPI). Each regression controls for region, year, and relative time. The standard errors are clustered at the region level.